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Original Research

Research on Carbon-Peak Prediction in Zhejiang's Manufacturing Sector from a Multi-Scenario Perspective Based on STIRPAT

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Abstract

Using China's "dual-carbon" targets as a reference, this paper focuses on Zhejiang's manufacturing sector as the research object and constructs a STIRPAT (stochastic impacts by regression on population, affluence, and technology)-based model to analyze the factors influencing carbon emissions associated with manufacturing and predict the peak emission levels. Among these influencing factors, investment-scale expansion and economic growth contribute to increases in carbon emissions, while energy-structure optimization and reduced carbon-emission intensity help restrain them. Notably, the economic level is identified as the predominant factor affecting carbon emissions. Among the nine proposed scenarios, scenario 6, characterized by "medium growth" and "high emission reduction", emerges as the most conducive to achieving high-quality and sustainable growth. Its carbon peak is projected for 2026, reaching 75.15 million tons of carbon dioxide emissions, making it the optimal model for Zhejiang's manufacturing sector. Based on the findings, two policy directions are proposed: optimize the energy-consumption structure and accelerate the development and use of low-carbon technologies. This research offers insights into carbon emissions in Zhejiang's manufacturing sector, presenting a blueprint for achieving a carbon peak and sustainable economic growth.

Keywords: STIRPAT, manufacturing industry, peak carbon dioxide emissions, scenario prediction

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Introduction

With rapid global economic development and accelerated industrialization, climate change has become increasingly serious. As the world's largest energy consumer and greenhouse gas emitter, China has pledged to achieve a carbon peak by 2030 and carbon neutrality by 2060 (the "dual- carbon" targets) [1], demonstrating its commitment to climate change mitigation and green, low-carbon, sustainable development. Zhejiang Province is one of the most economically active and developed regions in China; moreover, it has also established itself as a pioneer in carbon emission reduction reform. In recent years, the province has implemented green production; accelerated the adjustment, optimization, and upgrading of the industrial structure; and achieved significant results in carbon-emission reduction. In June 2021, Zhejiang took the lead by issuing the Zhejiang Province Carbon Peak and Carbon Neutrality Scientific and Technological Innovation Action Plan [2], aiming to achieve the dual-carbon targets ahead of time, by 2025 and 2030, respectively. In July of the same year, Zhejiang Province released the Guidelines for Carbon Emission Assessment of Construction Projects in Zhejiang Province (Trial) [3], making it the first province in China to carry out carbon assessment work across its entire area. Despite Zhejiang's pioneering efforts in establishing a low-carbon industrial system, promoting low-carbon clean energy, advocating for low-carbon lifestyles, and advancing regional low-carbon development, Zhejiang still faces two significant challenges under the backdrop of the "dual carbon" goal: the pressure exerted on production factor resources and constraints on market resources. As a major manufacturing province, Zhejiang faces several prominent problems, such as rapid growth in energy consumption, strong rigidity in energy demand, and imbalances in energy consumption within the manufacturing industry. Actively identifying factors affecting carbon emission reduction in Zhejiang's manufacturing sector and developing scientifically sound prediction methods for carbon emission peak scenarios in the province are not only essential for China to ensure it can conform to global development trends, but are also key to achieving sustainable development goals.

Research on the carbon peak has focused on identifying the key factors and exploring potential emission scenarios. Common methods include the Kaya constant equation, logarithmic mean Diels' index decomposition (LMDI), the environmental Kuznets curve, the Tapio method, and stochastic impacts by regression on population, affluence, and technology (STIRPAT).

Regarding the factors affecting carbon emissions, Kaya [4] proposed the Kaya constant equation and identified the different effects of factors such as the economy, policies, and population by linking them to anthropogenic CO_2 emissions. Based on this, Ang and Lee developed the LMDI method, which has the advantages of high flexibility, decomposition path independence, and no residual errors [5], and is widely used in the study of carbon emission driving factors [6, 7]. Shahbaz et al. [8] studied the relationship between economic growth and CO_2 emissions in Türkiye based on the EKC curve and found that energy intensity and economic growth increased CO_2 emissions, but the EKC model had obvious shortcomings in measurement and insufficient explanatory power [9]. Wang and Jiang [10] used the Tapio decoupling model to measure the elasticity of decoupling between China's economy and emissions; they found that the most significant factor for reducing CO_2 emissions was the investment effect, while labor input and economic structure were also contributors. Revising the IPAT (impact, population, affluence, and technology) model of Ehrlich and Holdren [11], Dietz and Rosa [12] proposed STIRPAT, which is useful for studying environmental issues as it introduces multiple independent variables to test their effect on environmental pressure. Chekouri et al. [13] found that population is a decisive factor in Algeria's CO_2 emissions, followed by energy use. Yildirim and Akin [14] noted that energy use is a worldwide pivot factor in CO_2 emissions. Based on the emission data of 23 OECD countries, it was discovered that a 1% increase in energy intensity, nonrenewable energy production, and renewable energy production leads to long-term increases in CO_2 emissions of 1.129%, 1.047%, and 0.032%, respectively. Li and Lu [15] used the STIRPAT model to quantify the potential of energy-service electrification in China based on the "electrifying energy use" strategy proposed by the State Grid Corporation of China. They indicated that when China's economic growth slows down, the potential for electrification growth will also slow down, but the level of technology can slow this decelerating trend.

Based on the STIRPAT model, Sidi et al. [16] studied the influencing factors of carbon dioxide emissions in Algeria in order to better curb carbon dioxide emissions and formulate a low-carbon development plan. The results show that population, energy use, urbanization, and affluence (GDP per capita) are the four major factors affecting carbon dioxide emissions. Tian et al. [17] analyzed the driving factors of energy consumption in rural areas of China's Henan province based on the STIRPAT model. The results show that effective irrigation area is the most important influence therefore; in addition, the growth of rural energy consumption in Henan province is also influenced by such factors as per capita living space, peasant household investment, agricultural machinery power, agricultural gross output value, and per capita income. Çağlar [18] investigated the determinants of emissions in the Turkish energy sector within the framework of the EKC and the STIRPAT model and found that economic level, population, and environmental patents increased emissions.

Regarding predicting peak carbon, Ge et al. [19] simulated emissions using the STIRPAT model and achieved high accuracy, with an average error of 1.78%. Thus, STIRPAT is a promising approach for predicting the time of peak carbon. Analyzing six emission scenarios in Beijing, Kang et al. [20] found that Beijing will not reach a carbon peak until 2035 unless cleaner production is applied, which could potentially achieve a carbon peak by 2030. Bai et al. [21] predicted that in the next decade, there will be a 1.5-fold increase in emissions in Baotou, which is a slower rate of increase than in the previous decade. Based on that finding and the identified factors, emission-reduction strategies, such as optimizing the industrial structure and improving agricultural production efficiency, are proposed. Based on the STIRPAT model, Feng et al. [22] conducted a scenario analysis of the synergistic effects of Yangtze River Delta air pollution control and carbon emission reduction. The results showed that the Yangtze River Delta could achieve synergistic emission reduction in the 2026 region; by 2030, the combined emission reduction of air pollution and carbon emissions will provide a reference for the decision-making process of promoting carbon reduction and further achieving carbon peak and carbon neutrality.

In summary, scholars have endeavored to construct diverse models utilizing various methodologies to examine the factors influencing carbon emissions and peak prediction. Concerning research methodologies, each approach possesses its own strengths and limitations. Notably, the STIRPAT method stands out as an efficacious technique for scrutinizing and comprehending the influence of intricate socio-economic factors on environmental stress owing to its commendable scalability. Particularly within the domain of carbon emissions research, the STIRPAT model proves instrumental in uncovering the primary driving forces behind carbon emissions. Furthermore, its integration with scenario analysis facilitates carbon emission predictions, a practice that has gained widespread acceptance. Across varying models, regions, and industries, the disparate research findings underscore the intricate nature of factors impacting carbon emissions, thereby presenting formidable challenges in forecasting carbon peaks. Furthermore, existing research exhibits certain inadequacies. Primarily, in terms of research scope, prior studies predominantly focused on national-level entities, with scant attention directed towards specific industries, thereby impeding the formulation and implementation of industry-level carbon peak policies by local governments. Regarding the selection of factors influencing carbon emissions, prevalent studies commonly consider parameters such as investment scale, economic growth rate, energy structure, and carbon emission intensity. Nevertheless, significant disparities persist in the identification of indicator variables and the methodologies employed for their measurement. Moreover, when establishing carbon emission scenarios, prevalent approaches rely heavily on deductive or empirical assessments grounded in historical data, with limited consideration given to national and local government imperatives concerning economic and social development planning, as well as energy conservation and carbon reduction policies. This tendency may engender disparities in the prediction outcomes regarding the carbon peak within the manufacturing industry, hence compromising the scientificity and feasibility of the carbon peak path. To fill these gaps, this study targets the manufacturing sector in Zhejiang Province using data for 2012–2021. Against the background of China's dual-carbon targets, STIRPAT is used to predict the time of the carbon peak, investigate potential emission-reduction pathways, and make policy suggestions.

Materials and Methods

CO_2 Emission Levels in the Manufacturing Sector

Referring to the baseline method described in the 2006 IPCC Guidelines for National Greenhouse Gas Inventories [23], carbon emissions in the manufacturing sector are calculated based on energy consumption. The statistical caliber of the manufacturing sector is based on the classification standards for energy consumption in industrial sub-sectors in the China Energy Statistical Yearbook, covering eight energy inputs including raw coal, coke, crude oil, natural gas, fuel oil, gasoline, kerosene, and diesel. The calculation formula is as follows:

$$I = \sum_{i=1}^{8} E_i \times NCV_i \times CEF_i \times COF_i \times \frac{44}{12} \tag{1}$$

where i represents energy type, and C, E, and NCV represent total carbon dioxide emissions, energy consumption, and average low calorific value, in units of million tons, million tons, and kilojoules/kg, respectively. CEF provides the carbon-emission factor for IPCC (2006), COF is the carbon oxidation factor (usually 1, according to IPCC), and 44/12 is the molecular weight ratio of CO_2 to C.

STIRPAT Model

Based on the classic IPAT model, Dietz and Rosa [12] proposed the STIRPAT (stochastic impacts by regression on population, affluence, and technology) model. STIRPAT has been widely used in the prediction of carbon peaks; its application expression is as follows:

$$lnI = a + blnP + clnA + dlnT + e \tag{2}$$

where I is the environmental effect (i.e., carbon emissions); P, A, and T represent population size, wealth, and technology level, respectively; a is the model coefficient; b, c, and d represent the elasticity coefficients of each indicator, which can be interpreted as the percentage of change in environmental impact owing to the change in P, A, and T; and e is the error term.

STIRPAT allows for the estimation of coefficients as parameters and the appropriate decomposition of factors [11]. Many studies have been conducted based on the above formula and have improved it according to research purposes [24, 25]. Grossman et al. [26], for example, suggested that in economic activities, scale, structure, and technological effects are the three major factors affecting environmental quality. Drawing on previous research and considering the characteristics and data availability of manufacturing in Zhejiang Province, this study extends the STIRPAT model and analyzes manufacturing-sector emissions based on the following factors:

(1) Investment scale (Q): Traditionally, the labor-intensive, high-energy-consuming nature of manufacturing led researchers to use the number of employees as a metric for industry size when investigating its effect on emissions [27, 28]. However, with advancements in artificial intelligence, big data, and industry development, there is an increasing emphasis on the manufacturing sector developing its unique carbon footprint. New technologies have made manufacturing processes more intelligent, automated, and digitized. Thus, the conventional approach of using the number of employees as an indicator is no longer suitable. Since Zhejiang's economy remains investment driven, increased fixed-asset investment is expected to cause the spatial spillover of emissions from high-emission manufacturing sectors, resulting in overall increases in carbon emissions [28]. Hence, the investment scale is selected as an indicator variable influencing carbon emissions, measured by the amount of fixed-asset investment [29-31].

(2) Economic level (U): With economic growth, the scale of manufacturing expands and production increases, thus increasing energy demand and consumption. Energy production and consumption are the main sources of carbon emissions in manufacturing, especially the burning of fossil fuels such as coal, oil, and natural gas, which produce a large amount of greenhouse gases such as carbon dioxide. Economic level is thus an important factor affecting emissions from the manufacturing sector. Referring to Wang et al. [32], Liu et al. [33], and Zhang [34], this study selects economic level as a main factor to measure carbon emissions, which are measured by per capita gross industrial output value.

(3) Energy structure (S): The choice of energy sources affects carbon emissions in the manufacturing industry; therefore, it is imperative for China to transition to a cleaner energy mix to achieve its dual-carbon targets [32]. Historically, manufacturing has relied heavily on fossil energy sources such as coal, crude oil, natural gas, and fuel oil, with coal contributing the most to emissions [33]. Emission-control systems aim to curtail the consumption of coal-based energy and promote the growth of clean energy, which can meet development needs while also aligning with dual-carbon targets. Referring to Zhang [34], Liu et al. [35], and Liu [36], this study includes the energy structure as one of the main factors in measuring carbon emissions, which is measured by the ratio of coal consumption to total primary energy consumption.

(4) Carbon-emission intensity (T): Technological innovation can provide economic benefits while also mitigating energy consumption and emissions through the introduction of low-carbon technologies. This contributes to energy conservation, emission reduction, and environmental improvement. To capture the effect of technology level on carbon emissions, previous studies used carbon-emission reduction intensity as a metric to gauge the development of low-carbon technology and examine its influence on emissions in manufacturing [32, 33]. Referring to the literature, this study includes carbon-emission intensity as one of the main factors in carbon-emission measurement; it is measured by the ratio of carbon emissions to the total output value of the manufacturing sector.

Based on the above, an extended STIRPAT model is obtained:

$$lnI = a + blnQ + clnU + dlnS + elnT + f \quad (3)$$

where I is the carbon emissions of the manufacturing industry, Q is the scale of investment, U is the economic level, S is the energy structure, and T is carbon-emission intensity.

Scenario Setting

The scenario setting is based on several factors related to industry development. The parameter values of the index variables of each factor in the model are used to simulate future development trends and evolution paths of carbon emissions. Based on China's dual-carbon targets and the completion of targets in Zhejiang's manufacturing sector from the 10th to 14th Five-Year Plan periods, with 2021 as the benchmark and 2022–2035 as the forecast period, the indexes of the four factors in the model are set to high, medium, and low change modes to estimate their scenario boundaries. The 10th Five-Year Plan refers to the "Outline of the 11th Five-Year Plan for the National Economic and Social Development of Zhejiang Province" (2001-2005), which aims to guide the government toward future development goals. The 11th, 12th, 13th, and 14th Five-Year Plans have the same connotations, with time spans of 2006-2010, 2011-2015, 2016-2020, and 2021-2025, respectively [37–41]. The estimation basis for each indicator variable is as follows:

(1) Estimation of investment scale indicator variables:

According to data from the Zhejiang Bureau of Statistics, fixed-asset investment in the manufacturing sector showed significant growth, rising from

530.54 billion yuan in 2012 to 1,172.00 billion yuan in 2021, for an average annual growth rate of 9.21%. Notably, during the 13th Five-Year Plan, the growth rate decreased to 5.75% compared with 12.62% during the 12th Five-Year Plan. During the 14th Five-Year Plan period, Zhejiang Province's investment focus is on accelerating the effectiveness of revitalizing manufacturing investment, guiding enterprises to actively deploy low-carbon and efficient manufacturing industries with high economic contribution and added value, as well as strategic emerging industries. Support enterprises in targeting high-end, intelligent, and green industries [42]. Consequently, the estimated fixed-asset investment is around 1,451.91 billion yuan, with an average annual growth rate of 6.5%, indicating a medium growth pattern. Additionally, aligning with the 14th Five-Year Plan's Goals for High-end Equipment Manufacturing in Zhejiang [43], which aim to establish a first-class international innovation and industrial highland, fixed-asset investment is projected to substantially increase, with an estimated average annual growth rate of 7.5%, representing a high-growth pattern. However, considering the current emphasis on energy conservation and emission reduction, future investment will be controlled to curb high-energy-consuming, high-emission projects. This includes accelerating the elimination of carbon-inefficient industries such as chemical fibers, textile printing and dyeing, and paper, aiming to eliminate backward production. As a result, the growth rate of fixed-asset investment is expected to decline, set at 5.5%, representing a low-growth model. In summary, the future scale of fixed-asset investment in Zhejiang's manufacturing sector is expected to show fluctuations.

(2) Estimation of economic level indicator variables:

As Zhejiang's economic development transitions to a new normal, characterized by a slowdown in the growth rate after more than 30 years of high growth, the province's GDP exhibited growth rates of 11%, 8.2%, and 6.5% during the 10th, 11th, and 13th Five-Year Plans, respectively. Specifically, the per capita industrial output value in manufacturing increased from 96.07 thousand yuan in 2012 to 134.48 thousand yuan in 2021, with an average annual growth rate of 3.81%. The growth rates during the 12th and 13th Five-Year Plans were 2.40% and 0.69%, indicating a steady increase in total volume but at a slower growth rate. In the upcoming 14th Five-Year Plan period, the province aims to exceed 8.5 trillion yuan and 130 thousand yuan for GDP and per capita GDP, respectively, striving for an average annual regional GDP growth rate of 5.5% or more. Additionally, the total output value of the equipment manufacturing industry is projected to surpass 4 trillion yuan. In achieving planning goals, the future per capita industrial output value of the manufacturing industry is expected to be about 136 thousand yuan, with a growth rate of 4.8%, establishing a medium-growth model. As Zhejiang Province further develops and reaches the level of medium-developed economies, its per capita GDP is expected to be about 150 thousand yuan, with a growth rate of 5.8%, establishing a high-growth model. Considering China's dual-carbon targets and Zhejiang's aim to "lead in achieving its carbon peak by 2030" amid the complexities of the volatile international market and increasing downward pressure on the economy, adjustments are being made to the growth pattern. The estimated per capita industrial output value of Zhejiang's manufacturing industry is around 126 thousand yuan, with a downward-adjusted growth rate of 3.8%, indicating a low growth pattern. In summary, the future per capita industrial output value of the manufacturing industry in Zhejiang Province is expected to exhibit a rising trend year by year.

(3) Estimation of energy structure indicator variables:

In Zhejiang Province, as a major consumer but minor producer of energy resources, coal consumption has historically held a significant position in the energy consumption structure, maintaining a share of around 60%. During the 12th Five-Year Plan period, the average annual growth rate of the proportion of coal consumption to total primary energy consumption increased by 4.38%, reflecting a high dependence on coal at that time. However, with the strengthening of environmental awareness and adjustments in the energy structure during the 13th Five-Year Plan period, the average annual decrease rate of this proportion reached 4.78%, demonstrating a clear optimization trend. Looking ahead, considering the opinions of the Central Committee of the Communist Party of China and the State Council on Fully, Accurately, and Comprehensively Implementing the New Development Philosophy and Doing Well in Carbon Peaking and Carbon Neutrality Work [44], which proposes that the share of non-fossil energy consumption should be around 20% by 2025 and around 25% by 2030, Zhejiang Province will further accelerate industrial restructuring and upgrading. It is estimated that the rate of decline in the proportion of coal consumption in Zhejiang Province in the future will be 6.5%, setting a high emissions reduction mode. However, with continued economic growth across the province, energy consumption will exhibit a period of rigid growth. At present, traditional manufacturing and high-energy-consuming industries account for a relatively high proportion, indicating significant potential for energy conservation and emission reduction in the future. Referring to the 14th Five-Year Plan for Energy Development in Zhejiang Province [45] and the "dual-carbon" goals, it is estimated that the rate of decline in the total coal consumption of the manufacturing industry in the future will be 5.5%, setting a low emissions reduction mode. Taking the average of the low and high emissions reduction modes, a moderate emissions reduction mode is established.

(4) Estimation of carbon intensity indicator variables:

During the 12th and 13th Five-Year Plan periods, carbon emissions per unit of GDP in Zhejiang Province decreased by 19% and 20.5%, respectively, achieving national emission-control targets. Carbon emissions per unit of output value in the manufacturing sector decreased from 1.24 t/10 thousand yuan in 2012 to 0.82 t/10 thousand yuan in 2021, with an average decline of 4.61%. During the 12^{th} and 13^{th} Five-Year Plan periods, the average annual decline rate of carbon intensity was 4.57% and 2.00%, respectively. After the 14^{th} Five-Year Plan, the potential for emission reduction through energy supply structure adjustment will be limited; thus, emission reduction in the manufacturing industry in the whole province will face increasing difficulties and pressure, and the rate of carbon intensity decline will also slow down. According to the calculation of an annual decline rate of 3%, it is estimated that carbon emissions per unit of output value in the 14^{th} Five-Year Plan period will decrease to 0.74t/10 thousand yuan, and a low emission-reduction mode will be set. During the 14^{th} Five-Year Plan period, the national target for the carbon intensity reduction rate in Zhejiang is not less than 20.5%. The Implementation Opinions on Completely, Accurately, and Comprehensively Adhering to New Development Concepts to Do a Good Job of Carbon Dioxide Emission Reduction and Carbon Neutrality Work [46], issued by Zhejiang Province, propose that by 2030, carbon emissions per unit of GDP will decrease by more than 65% compared with 2005. Based on these target constraints and the future acceleration of carbon-emission controls in Zhejiang, carbon intensity is expected to significantly improve, with an average annual decline rate of 5%. Further, carbon emissions per unit of output value will decrease to 0.68 t/10 thousand yuan, thus setting a high emission-reduction mode. Taking the average value of low and high emission reductions, a medium emission reduction mode is set with an average annual decline rate of 4%. Since carbon intensity is directly affected by coal consumption and GDP, there might be some fluctuations in its increase or decrease rate in the future.

Based on the above discussion, it is evident that the values of investment scale and economic level exhibit an increasing trend over time, while the values of energy structure and carbon emission intensity continuously decrease over time. Consequently, the four influencing factors – investment scale, economic level, energy structure, and carbon emission intensity – have been categorized into two groups for scenario configuration. Investment scale and economic level are grouped as industrial development indicators, given the general principles of economic development and market regulation, where an increase in investment scale and economic level is likely to lead to an increase in carbon emissions; while energy structure and carbon emission intensity are categorized as energy consumption indicators, under the premise of not considering the interaction among different factors, the optimization of energy structure and the reduction of carbon emission intensity can effectively restrain carbon emissions. Furthermore, based on estimated parameter values for each indicator variable, high, medium, and low values are assigned to the indicators, and through permutation and combination, nine scenarios for carbon emissions in the manufacturing industry of Zhejiang province are derived, as shown in Table 1.

Table 1. Carbon emission scenarios with different levels for the manufacturing sector.

Parameters	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9
Scale of investment	High	High	High	Medium	Medium	Medium	Low	Low	Low
Economic growth rate	High	High	High	Medium	Medium	Medium	Low	Low	Low
Energy structure	Low	Medium	High	Low	Medium	High	Low	Medium	High
Carbon intensity	Low	Medium	High	Low	Medium	High	Low	Medium	High

Table 2. The definitions and sources for the variables used in the extended STIRPAT model.

Variable	Notation	Definitions of Variables	Units	Source
Carbon emissions	I	Total CO_2 emissions from manufacturing industry	Million tons	CEADs
Investment scale	Q	Fixed assets investment in the manufacturing industry	Billion	Zhejiang Provincial Bureau of Statistics
Economic level	U	Total industrial output value/ Resident population	10 thousand yuan/ 10 thousand people	Zhejiang Provincial Bureau of Statistics
Energy structure	S	Coal consumption/ Total energy consumption	%	Zhejiang Provincial Bureau of Statistics
Carbon emission intensity	T	Carbon emissions/ Total industrial output value	Tons/ 10 thousand yuan	Zhejiang Provincial Bureau of Statistics

Data Sources

Taking Zhejiang's manufacturing sector from 2012 to 2021 as the research sample, energy consumption data for manufacturing terminals in the China Emission Accounts and Datasets (CEADs) are used to estimate its carbon emissions. The carbon-emission coefficient is taken from the guidelines for national greenhouse gas inventories issued by the IPCC in 2006, and the accounting results are reliable. In addition, the data used to measure investment scale, economic level, energy structure, carbon-emission intensity, and other indicators come from Zhejiang Province's statistical yearbooks over the years. Table 2 presents the variable descriptions.

Results and Discussion

Collinearity Test

Demonstrating the effectiveness of the prediction model requires multicollinearity processing. Multicollinearity refers to the correlation between multiple independent variables during regression calculation, which can make the model's coefficients lose practical significance. All of the above variable data are logarithmized, and historical data from 2012 to 2021 are analyzed using SPSS to conduct multiple linear regression and collinearity tests. Tables 3-5 show the results.

We can see in Tables 3 and 4 that the correlation coefficient R is 0.982, which is close to 1, indicating a strong correlation between variables. The goodness-of-fit R^2 is 0.964, and the adjusted R^2 is 0.935. This means that the four independent variables – investment scale, economic level, energy structure, and carbon-emission intensity – can explain 93.5% of the variation in the dependent variable (carbon emissions), and the significance coefficient is 0.001, indicating a significant result. We can see that the regression fitting effect of the STIRPAT model is good; however, we can see in Table 5 that the variance inflation factor (VIF) of all of the variables is significantly greater than 10, indicating strong multicollinearity between variables.

Table 3. Summary of models.

Parameters	Values
R	0.982
R^2	0.964
Adjusted	0.935
Errors in standardized estimates	0.106

Ridge Regression Analysis

There are several methods for addressing multicollinearity, including the least-squares method, the partial least-squares method, and ridge regression. Among them, ridge regression has strong generalization ability and reliability. Therefore, this study uses ridge regression to re-regress the data, obtain the ridge trace map, and change the trend of the determination coefficient, as shown in Fig. 1 and 2, where R^2 is the goodness of fit of the STIRPAT model and K is the ridge regression parameter.

The key to ridge regression is determining an appropriate ridge regression parameter, K. The K value is negatively correlated with R^2, meaning that as the K value decreases, R^2 increases. Therefore, we should choose a smaller K value while ensuring that the ridge trace curve gradually stabilizes and that the corresponding R^2 in the graph of R^2 versus K is at a relatively high level. In Fig. 1, we can see that when the K value is set to 0.02, the regression coefficients of the variables start to stabilize, and the R^2 value is relatively large, indicating the best fit of the model. Subsequently, ridge regression is conducted; Tables 6 and 7 show the results.

Based on the obtained results, the goodness-of-fit R^2 value is 0.829. This suggests that the selected independent variables can elucidate approximately 82.9% of the variations in carbon emissions in Zhejiang Province. The F-statistic value of 6.075, with a significance coefficient of 0.037, indicates that the independent variables have passed the significance test at the 5% level, signifying a better-fitting model. Therefore, the STIRPAT model is as follows:

$$\ln I = 6.857 + 0.045\ln Q + 0.355\ln U - 0.089\ln S + 0.227\ln T \tag{4}$$

From Equation (4), we can see that each variable influences carbon emissions in the order of economic level, carbon-emission intensity, energy structure, and investment scale. Among them, every 1% increase in investment scale will lead to a 0.045% increase

Table 4. Analysis of variance.

Model	Sum of squares	Degrees of freedom	Mean square	F	Significance
Regression	0.005	4	0.001	33.385	0.001
Residual	0.000	5	0.000		
Total	0.005	9			

Table 5. Results of multicollinearity analysis.

Parameters	Non-standardized coefficient		Standardized factor	T-test	P	Covariance statistic	
	Regression coefficient	Standard error				Tolerances	VIF**
Constant ()	-2.847	2.812		-1.012	0.358		
lnQ*	0.363	0.148	2.899	2.449	0.058	0.005	193.928
lnU	0.902	0.148	3.625	6.099	0.002	0.020	48.907
lnS	-0.004	0.040	-0.059	-0.107	0.919	0.023	42.818
lnT	1.135	0.241	5.790	4.705	0.005	0.005	209.684

*: Q is the scale of investment, U is the economic growth rate, S is the energy mix, and T is the carbon emission intensity. **: variance inflation factor

in the carbon emissions of Zhejiang's manufacturing sector, indicating that investment scale positively affects carbon emissions. When the investment scale increases, the production activities of the manufacturing industry might increase, thus increasing energy consumption and emissions. However, as we can see from the coefficient, the effect of investment scale on carbon emissions is small, which might be because manufacturing investment in Zhejiang mainly aims to improve energy efficiency, technological progress, and the industrial structure. The overall effect of multiple factors has helped manufacturing develop in a greener and lower carbon direction. Every 1% increase in the economic level will increase manufacturing-sector emissions by 0.355%, indicating that the economic level has a significant positive effect on carbon emissions. As the economy improves, production and consumption activities in the manufacturing sector typically increase, which can lead to more energy consumption and emissions. The economic level is thus an important factor affecting carbon emissions. Each 1% reduction in energy structure will lead to a 0.089% reduction in carbon emissions in Zhejiang's manufacturing industry, indicating that energy-structure optimization has a significant negative effect on carbon emissions. Energy-structure optimization is an important way to achieve the dual-carbon targets. Every 1% increase in carbon-emission intensity will lead to a 0.227% increase in emissions in Zhejiang's manufacturing sector. This indicates that carbon-emission intensity has a significant positive effect on carbon emissions, and carbon-emission intensity can be reduced through policy adjustments and technological progress.

To test the model's goodness of fit and ensure that it can accurately predict carbon emissions in Zhejiang Province, the values of the independent variables from 2012 to 2021 are substituted into Equation (4) for error testing. The error ratio between the fitted value and the actual value is calculated, and then the actual carbon emissions and the model-fitting results are obtained. As shown in Fig. 3, actual carbon emissions in 2014 were 66.76 million tons, while simulated carbon emissions were 67.23 million tons, with an absolute error ratio of 1%. Actual emissions in 2016 were 66.83 million

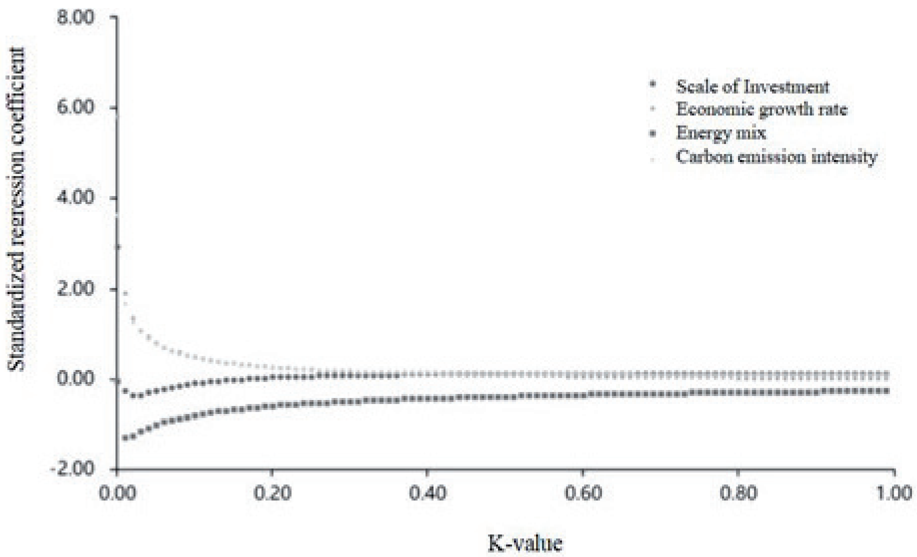

Fig. 1. Ridge plot of factors affecting carbon emissions in the manufacturing industry of Zhejiang Province.

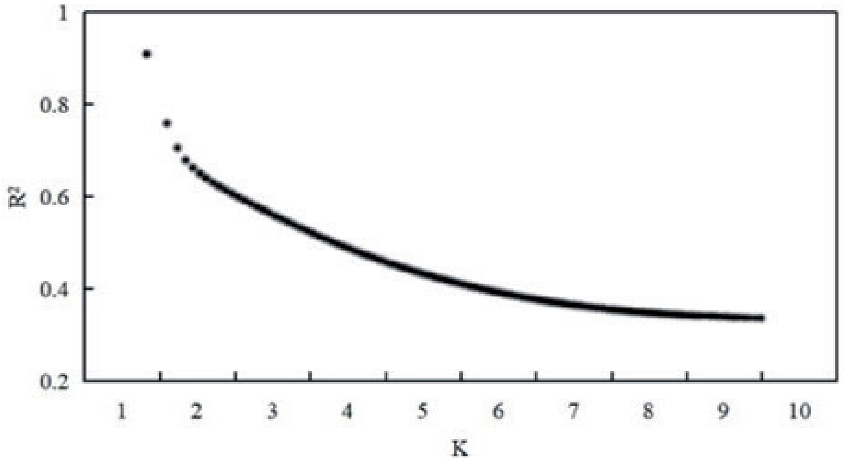

Fig. 2. R^2 plot corresponding to k value.

Table 6. Ridge Regression Models.

Parameters	Values
R	0.910
R^2	0.829
F	6.075
Sig F	0.037

tons, and the simulated emissions were 67.59 million tons, with an absolute error ratio of 1.13%. Actual 2020 emissions were 67.50 million tons, while the simulated emissions were 69.24 million tons, with an absolute error ratio of 2.52%. The absolute error ratios of other years are all within 1%, indicating that the model simulation results have a good correlation, and the simulated values basically match the actual values, indicating that it has practical simulation significance. Therefore, Equation (4) can be used to predict potential carbon emissions in Zhejiang's manufacturing sector.

Predicting Peak Carbon

Using the future development mode settings, the values of the abovementioned indicator variables are inserted into the model (Equation 4) to generate a carbon-peak path diagram for Zhejiang's manufacturing industry, as shown in Fig. 4.

According to the predicted results, the trend of carbon emissions in Zhejiang's manufacturing sector shows significant heterogeneity under different scenarios. Based on the characteristics shown in Fig. 4, the nine scenarios can be divided into three groups.

First, scenarios 1, 2, and 3 (the first group) are compared. In terms of scenario settings, all three scenarios have high growth rates for industrial development indicators, while the energy-consumption indicators are low emission reduction, medium emission reduction, and high emission reduction. From the trend of carbon emissions under scenario 1, the emissions of Zhejiang's manufacturing sector show an overall upward trend. There is a significant turning point in 2025,

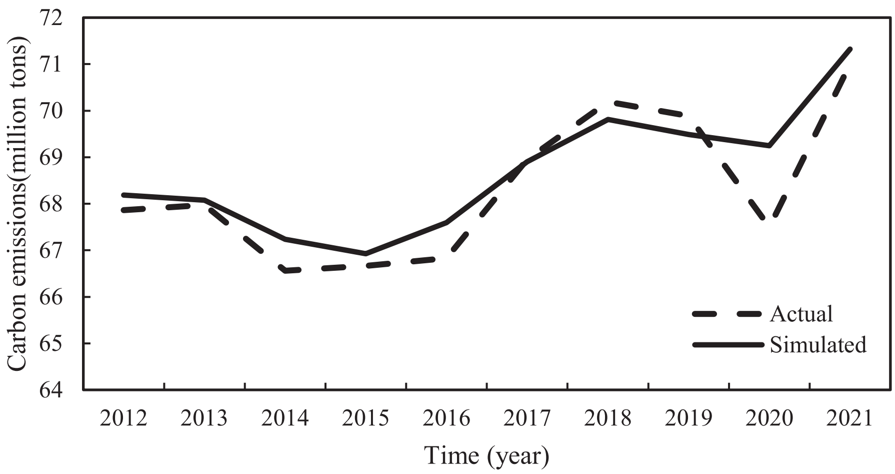

Fig. 3. Zhejiang's Actual Carbon Emissions from 2012 to 2021 and STIRPAT Model Simulation of Carbon Emissions.

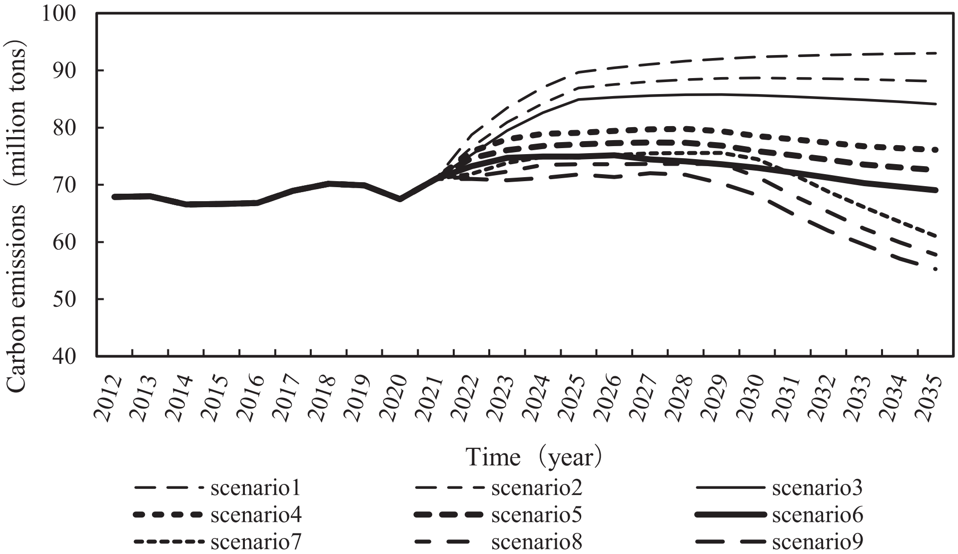

Fig. 4. Trends in future carbon emissions of Zhejiang Province's manufacturing industry under different scenarios.

with emissions rising sharply from 78.74 million tons in 2022 to 89.69 million tons in 2025 and then gradually slowing down until 92.99 million tons in 2035. Under scenarios 2 and 3, emissions show a trend of rapid increase followed by a slow decline, with peak values of 88.69 million tons and 85.78 million tons, respectively. Looking at peak time during the forecast period, scenario 1's emissions are on the rise, failing to achieve a carbon peak. Although scenario 2 has a peak, it is in 2030, thus failing to meet Zhejiang's aim to achieve a carbon peak before 2030. Scenario 3 reaches its carbon peak in 2029, consistent with the policy goal. We can speculate that under scenarios 1 and 2, high industry growth causes emissions to increase at a faster rate than carbon-reduction efforts, and the carbon peak will be delayed or not achieved. Therefore, those two scenarios reflect unsustainable development models.

Second, comparing the second group (scenarios 4, 5, and 6), the industrial development indicators of the three scenarios are all medium growth, and the energy-consumption indicators are low emission reduction, medium emission reduction, and high emission reduction. In terms of carbon-emission trends, the emissions of Zhejiang's manufacturing industry show a trend of slow increase followed by gentle decline, with peak values of 79.77 million tons, 77.39 million tons, and 75.15 million tons. In terms of peak time, during the forecast period, the peak years of scenarios 1, 2, and 3 are 2028, 2027, and 2026, respectively, all consistent with policy goals. In addition, compared with the first group, carbon emissions in this group of scenarios show a clear downward trend, and the peak time is advanced. We can speculate that the decrease in industrial development indicators suppresses emissions in Zhejiang's manufacturing industry and accelerates the carbon peak. First, the decrease in investment scale might limit expanding manufacturing enterprises' production capacity, thereby reducing energy consumption and reducing carbon-peak time. Especially in traditional manufacturing, which has high energy consumption and emissions, the decrease in investment scale might lead enterprises to reduce their investment in high-pollution, high-emission equipment and technologies, thereby reducing carbon emissions. Second, the slowdown in economic levels could slow down market demand, thereby reducing manufacturing production and emissions. At the same time, enterprises are more inclined to adopt environmentally friendly production methods and technologies to achieve sustainable development. As a result, carbon emissions from the production process are reduced, and the peak time is correspondingly advanced.

Table 7. Ridge regression model coefficients.

Parameters	Coefficient	Standard error	Standardized factor
Constant	6.857	1.015	0
*lnQ**	0.045	0.052	0.361
lnU	0.355	0.106	1.425
lnS	-0.089	0.026	-1.192
lnT	0.277	0.078	1.412

Finally, scenarios 7, 8, and 9 (the third group) are compared. In terms of scenario settings, the industrial development indicators of the three models are all high growth, and the energy-consumption indicators are low emission reduction, medium emission reduction, and high emission reduction. In terms of carbon-emission trends, under scenarios 7, 8, and 9, the emissions of Zhejiang's manufacturing sector show a trend of gentle increase followed by a rapid decrease, with peak values of 75.57 million tons, 73.64 million tons, and 71.75 million tons, respectively. In terms of peak time, during the forecast period, the peak years of scenarios 1, 2, and 3 are 2029, 2029, and 2028, respectively, consistent with policy expectations. In addition, compared with the previous two groups, overall, emissions in this group of scenarios continue to show a clear downward trend, but the peak time is between that of the first group and the second. We can speculate that when the industrial development indicators exceed a certain range and continue to decrease, it could have negative effects on Zhejiang's manufacturing industry. First, a significant decrease in investment scale might limit the development of the manufacturing industry and restrict production capacity expansion. This could make it difficult for manufacturing enterprises to promptly upgrade equipment and technologies, thereby affecting carbon-emission reductions. In addition, if enterprises cannot obtain sufficient financial support, it might also make it difficult for them to bear the cost of carbon-emission reduction, thus further affecting carbon-emission reduction. Second, under the low economic level mode, the process of optimizing and adjusting the industrial structure is hindered. In particular, some high-energy-consuming, high-emission industries might continue to occupy important positions in the sector. Economic weakness might also lead to a decrease in R&D investment and an innovation lag in these enterprises. This will affect the development and application of new technologies, thereby delaying the carbon peak.

We can see that within each group of scenarios, with the industrial development indicators kept constant, as the energy-consumption indicators transition from low emission reduction to medium emission reduction and then to high emission reduction, the time to reach the carbon peak in Zhejiang's manufacturing sector continuously advances, and the peak value decreases accordingly. Among the three scenario groups, focusing on the peak value and time to reach the carbon peak, the turning point occurs the earliest when the industrial development indicators are set to medium growth. This is especially evident in scenario 6, where carbon emissions increase slightly from 73.23 million tons in 2022 to 75.13 million tons in 2026 and then gradually decline to 69.03 million tons in 2035. By comparison, this mode achieves the earliest peak time and has a lower peak value. Furthermore, in scenario 6, the medium growth of industrial development indicators is highly aligned with the goals of the 14th Five-Year Plan, which prioritizes high-quality development and achieving stability after reaching the carbon peak. The high emission reduction in the energy-consumption indicators also aligns with the national dual-carbon policy and the current energy-consumption structure of Zhejiang's manufacturing industry. The aim is to further strengthen policies supporting energy conservation and emission reduction, guide enterprises to optimize the energy-consumption structure, improve carbon-emission intensity, and significantly reduce emissions. This scenario aims to ensure stable growth in economic development and per capita output value through intensive development. It is a highly feasible model for high-quality, sustainable growth. In conclusion, scenario 6 should be prioritized as a development model for achieving the carbon peak in Zhejiang's manufacturing sector.

Conclusions

Based on the actual development of Zhejiang's manufacturing sector, this study first extracts two industrial development indicators (investment scale and economic level) and two energy-consumption indicators (energy structure and carbon-emission intensity). Among them, investment-scale expansion and economic growth will promote the development of Zhejiang's manufacturing sector but will also increase carbon emissions. Energy-structure optimization and reduced carbon-emission intensity can restrain carbon-emission reduction, which is an important breakthrough for achieving a carbon peak.

Using data spanning 2012-2021 for Zhejiang Province, this study uses an enhanced STIRPAT model to predict and analyze peak carbon emissions in the manufacturing sector. First, two industrial development indicators (investigation scale and economic level) and two energy-consumption indicators (energy structure and carbon-emission intensity) are proposed. Expanding the investment scale and raising the economic level will promote the development of Zhejiang's manufacturing sector but increase emissions. Meanwhile, energy-structure optimization and reduced carbon-emission intensity will restrain carbon-emission reduction, which is also important for promoting carbon-peak achievement. Further, based on STIRPAT and data from the last decade, this study analyzes nine potential scenarios for reaching the carbon peak and concludes the following:

Among the four factors influencing carbon emissions, investment-scale expansion and economic growth have boosting effects, while energy-structure optimization and improved carbon-emission intensity have suppressing effects. A 1% change in investment scale, economic level, energy structure, and carbon-emission intensity results in 0.045%, 0.355%, −0.089%, and 0.227% changes in emissions in Zhejiang's manufacturing sector. Notably, the economic level has the most substantial effect on carbon emissions.

Among the nine carbon-emission scenarios, scenario 6 achieves a carbon peak in 2026, reaching a peak value of 75.15 million tons. This scenario mitigates the boosting effect of fixed investment on emissions, reinforces the inhibiting effect of energy-structure optimization and low-carbon technology adoption, and reflects the expectation of stable economic development. This alignment with the concept of high-quality development makes it the preferred model for Zhejiang's manufacturing sector to lead in the achievement of the carbon peak.

These findings can guide the development of emission-reduction policies and promote environmentally conscious, low-carbon, sustainable growth in the manufacturing industry. Based on the above, two suggestions are proposed in terms of energy structure and carbon-emission intensity, aiming to provide a decision-making reference for the green, low-carbon, sustainable development of manufacturing.

(1) Optimize the energy-consumption structure. Promote energy-structure adjustment based on the characteristics and development trends of manufacturing industries in different regions. Implement pollution-reduction and carbon-reduction actions in the key areas of manufacturing, controlling the total amount of fossil energy while ensuring sustainable economic development. Strengthen energy-saving and emission-reduction transformations in high-energy-consumption and high-pollution industries such as steel and chemicals. Reduce excessive energy consumption and pollution in these industries' production processes, and reduce reliance on nonrenewable energy sources. Improve the carbon-emission system, enhance the environmental protection and carbon-emission regulation of manufacturing enterprises, and comprehensively manage and control carbon emissions. Advocate for the implementation of circular economy models in manufacturing enterprises, emphasizing the recycling of resources and the reduction of waste. Through the use of waste resources and the closed-loop design of industrial chains, we can reduce reliance on raw materials, decrease emissions and pollution, and ensure the coordinated development of the manufacturing industry and environmental protection.

(2) Accelerate R&D on low-carbon technologies. Increase investment in R&D in the manufacturing sector; expedite R&D on high-efficiency, energy-saving technologies, and advanced equipment technologies; and promote the development and use of zero-carbon energy technologies and renewable energy. Strengthen technology-driven, intelligent manufacturing and digitalization services; use information technology to build a digital platform; dig deeper into the digital potential of the green transformation of the manufacturing industry; enhance the effectiveness of emission reduction in the traditional manufacturing industries of textiles and chemicals; and create a more environmentally friendly industrial chain. At the same time, continue to increase the share of high-tech, low-emission, high-end manufacturing industries such as artificial intelligence, integrated circuits, computer networks, and communication equipment. Focus on building several provincial low-carbon industrial bases with distinctive features, strong product competitiveness, and high levels of innovation to promote the optimization and upgrading of the industrial structure of the manufacturing industry. Accelerate the transformation of the manufacturing sector into a low-carbon, intelligent, and servicing-oriented industry.

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Conflict of Interest

The authors declare no conflict of interest.

References

1. Opinions of the CPC Central Committee and the State Council on completely, accurately and Comprehensively Implementing the New Development Concept and Doing Well in Carbon Peak and Carbon Neutrality Work. Available online: https://www.gov.cn/gongbao/content/2021/content_5649728.htm (accessed on: 24 October **2021**).
2. Zhejiang Province Carbon Peak and Carbon Neutrality Scientific and Technological Innovation Action Plan. Available online: https://www.most.gov.cn/dfkj/zj/zxdt/202106/t20210618_175262.html (accessed on: 18 June **2021**).
3. Notice from the Zhejiang Provincial Department of Ecology and Environment on the Issuance and Implementation of the "Guidelines for Carbon Emission Assessment of Construction Projects in Zhejiang Province (Trial)". Available online: http://sthjt.zj.gov.cn/art/2021/7/8/art_1229263469_2310637.html (accessed on: 8 July **2021**).
4. KAYA Y. Impact of Carbon Dioxide Emission on GNP Growth: Interpretation of Proposed Scenarios, Presentation to the Energy and Industry Subgroup. Response Strategies Working Group, IPCC, Paris. **1989**.
5. ANG B.W., LEE S.Y. Decomposition of Industrial Energy Consumption: Some Methodological and Application Issues. Energy Economics. **16** (2), 83, **1994**.
6. MA T., ZHANG X., LIU J., LIANG Y. Quantifying the Drivers of Carbon Emissions in China's Construction Industry: A Decomposition Analysis Based on the LMDI Method. Journal of Cleaner Production. **228**, 1067, **2019**.
7. DONG K., SUN R., LI J. Decomposition Analysis of Energy-related Carbon Emissions and Influencing Factors

in China: An Empirical Study Using the LMDI Method. Energy Economics. **81**, 475, **2019**.
8. SHAHBAZ M., OZTURK I., AFZA T., ALI A. Revisiting the Environmental Kuznets Curve in a Global Economy. Renewable and Sustainable Energy Reviews. **25**, 494, **2013**.
9. ZHANG J.L., LIU L.P. Review of Application of Prediction Models of Regional Carbon Emission in China. Environmental Science Survey. **38** (4), 15, **2019**.
10. WANG Q., JIANG R. Is China's Economic Growth Decoupled from Carbon Emissions. Journal of Cleaner Production. **225**, 1194, **2019**.
11. EHRLICH P.R., HOLDREN J.P. Impact of Population Growth. Science. **171** (3977), 1212, **1971**.
12. DIETZ T., ROSA E.A. Rethinking the Environmental Impacts of Population Affluence and Technology. Human Ecology Review. **2** (1), 277, **1994**.
13. CHEKOURI S.M., CHIBI A., BENBOUZIANE M. Examining the Driving Factors of CO_2 Emissions Using the STIRPAT Model: the Case of Algeria. International Journal of Sustainable Energy. **39** (10), 927, **2020**.
14. YILDIRIM K., AKIN T. The Analysis of the Relationship Between Energy Resources and CO_2 Emissions in OECD Countries with the STIRPAT Model. Journal of Yasar University. **18** (71), 316, **2023**.
15. LI Y., LU S. The Potential of Electrifying China's Energy Use: an Analysis Based on STIRPAT Model. Polish Journal of Environmental Studies. **30** (3), 2173, **2021**.
16. SIDI M.C., ABDERRAHIM C., MOHAMED B. Examining the Driving Factors of CO_2 Emissions Using the STIRPAT Model: the Case of Algeria. International Journal of Sustainable Energy. **39** (10), 927, **2020**.
17. TIAN C.Z., PENG L., SHAO H.Y., LI M., ZHENG Y.L. Analysis of Driving Forces of Energy Consumption in Rural Areas of China's Henan Province Based on the STIRPAT Model and Ridge Regression. Polish Journal of Environmental Studies. **29** (2), 1391, **2020**.
18. ÇAĞLAR A.E. The Role of Environmental Patents in Environmental Kuznets Curve Hypothesis in Turkey: Evidence from the Augmented ARDL. **15** (4), 913, **2022**.
19. GE X.L., WANG Y., ZHU H.Q., DING Z.Q. Analysis and Forecast of the Tianjin Industrial Carbon Dioxide Emissions Resulted from Energy Consumption. International Journal of Sustainable Energy. **36** (7), 637, **2017**.
20. KANG L.G., CAO Z.L., LIU W., WU X.J., YANG Y., YUAN X.X., WANG W.J., ZHAO W. Prediction of Carbon Peak in Beiiing-Tianjin-Hebei Region Based on STIRPAT Model. Journal of Hebei University of Science and Technology. **44** (4), 421, **2023**.
21. BAI Y., ZHANG Y. Carbon Emission Growth Mechanism and Trend Forecast in Baotou based on Production-Living-Ecological Space. Polish Journal of Environmental Studies. **32** (5), 4471, **2023**.
22. FENG P.J., GU Y., YU Y.G., BAO Y.Z., GAO R.Y., NI T.H. Scenario Analysis on Co-benefits of Air Pollution Control and Carbon Reduction in Yangtze River Delta Based on STIRPAT Model. PLOS ONE. **19** (1), **2024**.
23. EGGLESTON H.S., BUENDIA L., MIWA K., NGARA T., TANABE K. 2006 IPCC Guidelines for National Greenhouse Gas Inventories. National Greenhouse Gas Inventories Programme; IGES, Japan. **2006**.
24. DIETZ T., ROSA E.A. Effects of Population and Affluence on CO_2 Emissions. Proceedings of the National Academy of Sciences of the USA. **94** (1), 175, **1997**.
25. YORK R., ROSA E.A., DIETZ T. STIRPAT, IPAT and ImPACT: Analytic Tools for Unpacking the Driving Forces of Environmental Impacts. Ecological Economics. **46** (3), 351, **2003**.
26. GROSSMAN G.M., KRUEGER A.B. Environmental Impacts of a North American Free Trade Agreement. NBER Working Paper. **1991**.
27. YANG M., LU X., DUAN H.B. Analysis on the Determinants and Peaking Paths of CO_2, Emissions in China's High Energy-Consuming Industries. Systems Engineering – Theory & Practice. **38** (10), 2501, **2018**.
28. FU H., LI G.P., ZHU T. Carbon Emission of China's Manufacturing Industry: Industry Differences and Decomposition of Driving Factors. Reform. **5**, 38, **2021**.
29. WANG X., ZHANG L.J., QIN Y.C. Spatiotemporal Changes of Carbon Emissions in High-Carbo Manufacturing Industry in China and Driving Factors. Resources Science. **42** (2), 323, **2020**.
30. XU S.C., ZHANG L., LIU Y.T., ZHANG W.W., HE Z.X., LONG R.Y., CHEN, H. Determination of the Factors That Influence Increments in CO_2 Emissions in Jiangsu, China Using the SDA Method. Journal of Cleaner Production. **142**, 3061, **2017**.
31. QIONG W., RUI J. Is China's Economic Growth Decoupled From Carbon Emissions? Journal of Cleaner Production. **225**, 1194, **2019**.
32. WANG Y., BI Y., WANG E.D. Scene Prediction of Carbon Emission Peak and Emission Reduction Potential Estimation in Chinese Industry. China Population, Resources and Environment. **27** (10) , 131, **2017**.
33. LIU Q.C., LI Q., ZHENG X.X. The Prediction of Carbon Dioxide Emissions in Chongqing Based on Fossil Fuel Combustion. Acta Scientiae Circumstantiae. **37** (4), 1582, **2017**.
34. ZHANG C. Forecasting and Scenario Analysis of Industrial Carbon Emissions in Anhui Province Based on STIRPAT Model. Journal of Heilongiiang Institute of Technology. **36** (3), 40, **2022**.
35. LIU M.H., ZHAI H.X., LIU S.N., YUE Y.Y., YANG D.K., LI J. Comparative Analysis of Carbon Emissions in Tianjin based on LMDI Method and STIRPAT Model. Journal of Environmental Engineering Technology. **13** (1), 63, **2023**.
36. LIU X.Y. Study on Infuencing Factors of Carbon Emissions from Industrial Energy Consumption based on STIRPAT Model [J]. Ecological Economy. **35** (3), 27, **2019**.
37. The 10th Five Year Plan for National Economic and Social Development in Zhejiang Pro-vince. Available online: https://fzggw.zj.gov.cn/art/2012/4/1/art_1620990_35416079.html (accessed on 01 April **2012**).
38. The 11th Five Year Plan for National Economic and Social Development in Zhejiang Pro-vince. Available online: https://fzggw.zj.gov.cn/art/2013/11/18/art_1620990_35416122.html (accessed on 18 November **2013**).
39. The 12th Five Year Plan for National Economic and Social Development in Zhejiang Pro-vince. Available online: https://fzggw.zj.gov.cn/art/2021/6/18/art_1229539895_4666378.html (accessed on 18 June **2021**).
40. The 13th Five Year Plan for National Economic and Social Development in Zhejiang Pro-vince. Available online: https://fzggw.zj.gov.cn/art/2021/6/18/art_1229539892_4666286.html (accessed on 18 June **2021**).
41. Outline of the 14th Five-Year Plan (2021-2025) for National Economic and Social Devel-opment and Vision 2035 of the People's Republic of China. Available online: https://fzggw.zj.gov.cn/art/2021/2/23/art_1599544_58924918.html (accessed on 23 February **2021**).

42. Opinions of the Central Committee of the Communist Party of China and the State Counc-il on Supporting the High Quality Development and Construction of Zhejiang as a Demo-nstration Zone for Common Prosperity. Available online: https://www.gov.cn/zhengce/2021-06/10/content_5616833.htm (accessed on 10 June **2021**).
43. The 14th Five Year Plan for the Development of High-end Equipment Manufacturing Ind-ustry in Zhejiang Province. Available online: https://www.zj.gov.cn/art/2015/7/17/art_1229540821_4667007.html (accessed on 17 July **2015**).
44. Notice from the General Office of the People's Government of Zhejiang Province on the Issuance of the Zhejiang Province Energy Development "14th Five-Year Plan". Available online: https://www.zj.gov.cn/art/2022/5/19/art_1229019365_2404305.html. (accessed on 19 May **2022**).
45. Opinions of the Central Committee of the Communist Party of China and the State Council on Fully, Accurately, and Comprehensively Implementing the New Development Philosophy and Doing Well in Carbon Peaking and Carbon Neutrality Work. Available online: https://www.zj.gov.cn/art/2015/7/17/art_1229540821_4667007.html (accessed on 22 September **2021**).
46. Implementation Opinions of the Zhejiang Provincial Party Committee and Provincial Government on Fully, Accurately, and Comprehensively Implementing the New Development Concept and Doing Well in Carbon Peak and Carbon Neutrality Work. Available online: https://jst.zj.gov.cn/art/2022/2/17/art_1569971_58928904.html. (accessed on 19 May **2022**).