ISSN 2706-6827 Vol. 6, Issue 9: 84-90, DOI: 10.25236/IJFS.2024.060913

Decomposition of Energy Carbon Emission Factors and Scenario Prediction Based on Multiple Models

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Abstract: *China has actively formulated and implemented a series of policies to address climate change and actively promoted the green transformation of its economy. Therefore, this paper carries out adecomposition of energy carbon emission factors and realises scenario projections for Guangdong Province in order to promote scientific, efficient and targeted carbon emission reduction. Firstly, a measurement method proposed in IPCC(2006) is used to calculate Guangdong's energy consumption carbon emissions from 2000 to 2020. On this basis, based on the extended Kaya equation, the LMDI decomposition method is applied to quantitatively measure the carbon emissions of energy consumption in Guangdong, and to reveal the influence mechanism of each factor on energy consumption. In order to solve the problem of multiple co-linearity of factors in the STIRPAT prediction model, two types of regressions, Lasso regression and Ridge regression, we reused for fitting. Finally, through the analysis of the factors affecting the carbon emissions of China's energy system and the simulation of the scenarios, a decision basis is provided for the optimisation of the carbon emissions of China's energy system.*

Keywords: *Carbon emissions; LMDI; STIRPAT; Scenario projections*

1. Literature review and theoretical analysis

In this section, the application and literature of LMDI decomposition method and STIRPAT model are summarized, and the principle of factor decomposition and the estimation of energy carbon emission in Guangdong province are analyzed.

1.1. Literature review

1.1.1. LMDI decomposition

In order to achieve “Carbon peak” and “Carbon neutrality”, scholars have made a lot of achievements in studying the decomposition of carbon emission factors. Ang and Liu (2001) present a case study using additive LMDI for energy and carbon emissions [1] . Some scholars use LMDI decomposition method to study provinces and cities, such as Guangxi Province, Guizhou Province, Shaanxi Province, and Beijing City, the main factors selected are: resident population size, per capita income, energy prices, energy intensity, energy structure, industrial structure and economic development scale [2] . Liu Jinhua (2022) used LMDI decomposition model to decompose the carbon emission factors into economic level, population size, energy intensity, energy structure and industrial structure, and analyzed their influence on carbon emission one by one [3] .Fan Linzi (2022) estimated the energy factor of the carbon emission of the logistics industry, and used the generalized Kaya identity to analyze the carbon emission of the logistics industry, the contribution rate of six major influencing factors of carbon emission in logistics industry was obtained [4] . Wang Libing and Zhang Yun (2021) used the LMDI method to study the influencing factors of carbon emissions from energy consumption in China. In addition to commonly used factors such as economic scale, industrial structure, energy density, and energy structure, the increase in per capita disposable income was compared with the contribution rates of carbon emissions from the primary, secondary, and tertiary industries, as well as the residential sector. The results showed that economic growth was the biggest driving force, while energy density, industrial structure, and energy structure played a certain inhibitory role. [5]

1.1.2. STIRPAT model and scenario prediction

Richard et al. (2003) , using the STIRPAT model for the effects of transnational carbon emissions, showed that population has a proportional effect on CO2 emissions and energy footprint [11]. Using the STIRPAT extended model and ridge regression method, Guan Lijie et al. (2021) conducted a quantitative study on energy carbon emissions in Shanxi province, and constructed eight scenarios, the energy carbon emissions of Shanxi province from 2020 to 2050 are predicted, and the energy carbon emissions in the next 30 years are predicted [14] .

1.2. Theoretical basis

1.2.1. Carbon emission measurement

$$\mathrm{CO_2} = \sum_{i=1}^{8} \mathrm{E_i c_i f_i} * 44/12 \tag{1}$$

Based on the categories listed in the IPCC2006 National Greenhouse Gas emission inventory guidelines, and taking the energy consumption of major energy sources as the basis, the carbon emissions from energy sources in Guangdong province were calculated, according to the standard coal coefficient and carbon emission coefficient of the main energy sources, the carbon emission of energy sources in Guangdong province is determined, and the formula is shown as (1) .

In the formula (1) , CO2 is the carbon dioxide emission, and I denotes the eight main types of energy, namely coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil and natural gas EI is the energy consumption in the first place, CI is the conversion coefficient of standard coal, fi is the carbon emission coefficient of energy in the first place, and 44/12 is the conversion coefficient of carbon to carbon dioxide. The energy conversion standard coal coefficient and carbon emission coefficient are shown in table 1

Table 1: Carbon emission coefficient of fossil energy

Types of energy	energy equivalent to standard coal coefficient	Carbon emission factor
coal	0.1430	0.7559
coke	0.9714	0.8850
crude oil	1.4286	0.5857
gasoline	1.4714	0.5538
kerosene	1.4714	0.5714
diesel	1.4571	0.5919
fuel oil	1.4286	0.6185
natural gas	1.2150	0.4483

1.2.2. Basic principles of factor decomposition

The factor decomposition method is mainly used for energy and environment problems, which can be referred to the IPAT (impact, population, affluence, Technolog) environmental impact decomposition model constructed by Ehrlich and Kaya [16]

$$\text{Per capita CO2 emissions} = \text{GDP/population} \times \text{energy consumption/GDP} \times \text{CO2 emissions/energy consumption} \tag{2}$$

The first item on the right of formula (2) is GDP per capita, which is an economic factor. The second item is energy consumption density, which is a technical factor reflecting energy use. The third item is CO2 per unit of energy consumption, therefore also known as carbon coefficient, which is the unit of energy produced by the combustion of CO2. The increase of any one of the three factors will increase the per capita CO2 emission in the left-hand region.

2. Research Design

2.1. Variable selection

The data used in this paper are from China Energy Statistical Yearbook and Guangdong Statistical Yearbook to calculate the decomposition of energy carbon emission factors in Guangdong province. The study, conducted between 2000 and 2020, calculated Guangdong's energy carbon emissions based on consumption of eight types of energy-coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil and natural gas-over a 21-year period.The main selected variables for Guangdong's decomposition of energy carbon emission factors are energy consumption (E) , energy consumption output (GDP) , population size (p) , etc.

2.1.1. A machine learning model based on Lasso regression

Lasso regression is a loss function followed by L 1 regularization to avoid Multicollinearity. The loss function of Lasso regression is:

$$\min_{w} |X_W - Y|_2^2 + \alpha |W|_1 \tag{3}$$

In the formula (3) , Y is the independent variable, W is the model parameter, x is the dependent variable, and α is the regularization coefficient of Lasso regression.

2.1.2. Transference registration

This paper constructs ridge regression based on machine learning method:

$$\min_{w} |X_W - Y|_2^2 + \alpha |W|_2^2 \tag{4}$$

In the formula (4) , Y is the independent variable, W is the model parameter, x is the dependent variable and α is the ridge regression regularization coefficient. L2-regularization is the result of estimation by Maximum a posteriori estimation when the parameter W satisfies the normal distribution.

2.1.3. STIRPAT model

The basic form of the STIRPAT model is:

$$I_i = \alpha P_i^b A_i^c T_i^d e_i \tag{5}$$

Where I stands for environmental impact, P for population, a for per capita wealth, T for technology, a for model coefficients, and B, C, and D for parameters that are estimated, eI is a random error term, and I represents different observation units.

3. Empirical results and analysis

3.1. LMDI decomposition results

The decomposition formula (6) can be used to quantify the impact of five factors on carbon emissions: population, per capita GDP, industrial structure, energy intensity and energy structure, the calculation results of contribution degree and cumulative contribution degree of each influence factor.From 2000 to 2020, the contribution and cumulative contribution of the influencing factors of energy consumption carbon emissions in Guangdong province are shown in figure 1 and figure 2.

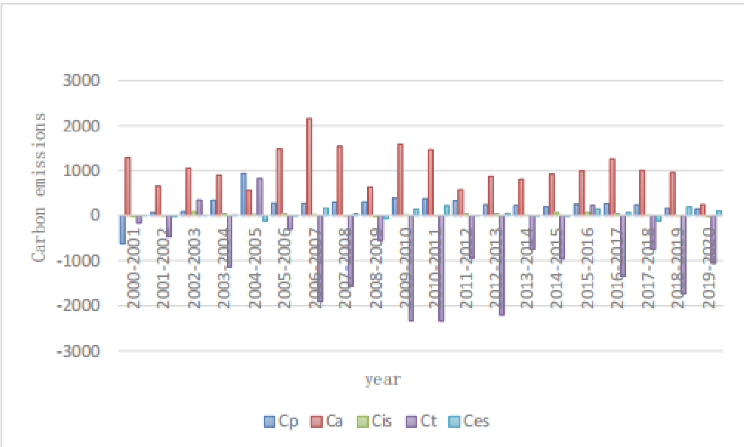

Figure 1: Contribution of influencing factors of energy consumption carbon emissions in Guangdong province from 2000 to 2020

ISSN 2706-6827 Vol. 6, Issue 9: 84-90, DOI: 10.25236/IJFS.2024.060913

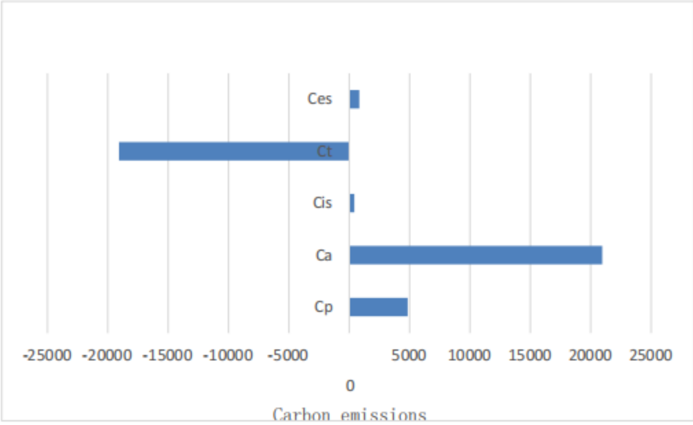

Figure 2: Contribution of influencing factors of energy consumption carbon emissions in Guangdong province from 2000 to 2020

$$\begin{cases} \Delta C_p = \sum_{i=1}^{3}\sum_{j=1}^{8}\frac{c_{ij}^T-c_{ij}^0}{lnc_{ij}^T-lnc_{ij}^0}ln(\frac{p^T}{p^0}) \\ \Delta C_a = \sum_{i=1}^{3}\sum_{j=1}^{8}\frac{c_{ij}^T-c_{ij}^0}{lnc_{ij}^T-lnc_{ij}^0}ln(\frac{a^T}{a^0}) \\ \Delta C_{t_i} = \sum_{i=1}^{3}\sum_{j=1}^{8}\frac{c_{ij}^T-c_{ij}^0}{lnc_{ij}^T-lnc_{ij}^0}ln(\frac{t_i^T}{t_i^0}) \\ \Delta C_{is_i} = \sum_{i=1}^{3}\sum_{j=1}^{8}\frac{c_{ij}^T-c_{ij}^0}{lnc_{ij}^T-lnc_{ij}^0}ln(\frac{is_i^T}{is_i^0}) \\ \Delta C_{es_{ij}} = \sum_{i=1}^{3}\sum_{j=1}^{8}\frac{c_{ij}^T-c_{ij}^0}{lnc_{ij}^T-lnc_{ij}^0}ln(\frac{es_{ij}^T}{es_{ij}^0}) \end{cases} \quad (6)$$

It determines the value of the parameter estimator by constructing the objective function, that is, the sum of squares of residuals, taking the parameter estimator of the model as a variable and minimizing the value of the function [17] . For the model shown in Formula (7) , the variables shown in table 2 were ordinary least squares to test for multiple linear regression and their regression models were analyzed.

$$InI = a + blnP + cInA + dInT + eInES + fInIS \quad (7)$$

Table 2: Variable names, symbols, definitions, and units

Variable name	Symbol	definition	unit
Independent variable			
Carbon emissions	*I*	Carbon emissions	Ten thousand tons
dependent variables			
Population size	P	Total resident population	Thousands
GDP per capita	A	Per capita GDP of Guangdong province	10,000 yuan/person
Energy intensity	T	A unit of GDP in Guangdong consumes energy	A ton of standard coal/Ten Thousand Yuan
Energy structure	ES	Energy carbon emission factor	Tons/tons of standard coal
Industrial structure	IS	Secondary sector of the economy value added as a percentage of GDP in the province	%

From the calculation results, it can be seen that the impact of various factors on carbon emissions are different: energy consumption intensity shows a negative effect on carbon emissions, energy structure, industrial structure, per capita GDP, population in general, the carbon emissions show a

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positive effect. The order of influence of energy consumption on energy consumption in Guangdong province from high to low is: per capita GDP of Guangdong province > energy consumption intensity > population size > energy structure > industrial structure.

3.2. Regression based on machine learning

Table 3: Ordinary least squares estimates values and true values based on ridge regression

	Unstandardized coefficients		Standardized coefficients	Collinearity statistics	
	B	Standard error	Beta	Tolerance	VIF
(Constant	-3.757E-13	0.000			
lnP	1.000	0.000	0.539	0.048	20.976
lnA	1.000	0.000	2.004	0.035	28.932
lnT	1.000	0.000	1.728	0.025	40.544
lnES	1.000	0.000	0.035	0.140	7.117
lnIS	-1.338E-14	0.000	0.000	0.180	5.549

Using SPSS26.0 software, based on the variables in table 2, the general least squares test of multiple linear regression was performed on the sequence data of the model shown in Formula (7) , the regression results are summarized in table 3. Figure 3 shows the comparison of machine learning values prediction.

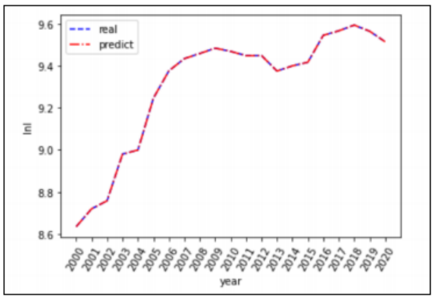

Figure 3: Comparison of machine learning prediction

The results of the regression showed that the VIF values of the three independent variables were greater than 10, so it was clear that there was a Multicollinearity problem with the variable data. In order to solve the problem of multiple collinearity, Lasso regression and ridge regression are used to fit the above data to eliminate the influence of multiple collinearity.

3.3. Cenario prediction of carbon emission based on STIRPAT model

In order to simulate the impact of different factors on carbon emissions in 2030, scenario analysis was applied to design high-carbon scenario, medium-carbon scenario and low-carbon scenario.

Table 4: Scenario forecasts the average annual growth rate of each parameter

	year	population	GDP per capita	Industrial structure	Energy intensity	Energy mix
High Carbon	2020-2025	0.20%	7.33%	-1.45%	-2.1%	-1%
	2026-2030	-0.15%	4.63%	-2.19%	-2.3%	-1.5%
Middle Carbon	2020-2025	0.15%	6.57%	-2.05%	-4.5%	-3%
	2026-2030	-0.29%	3.55%	-3.80%	-4.7%	-3.5%
Low Carbon	2020-2025	0.13%	5.87%	-2.84%	-6%	-5%
	2026-2030	-0.31%	3.55%	-4.10%	-6.2%	-5.5%

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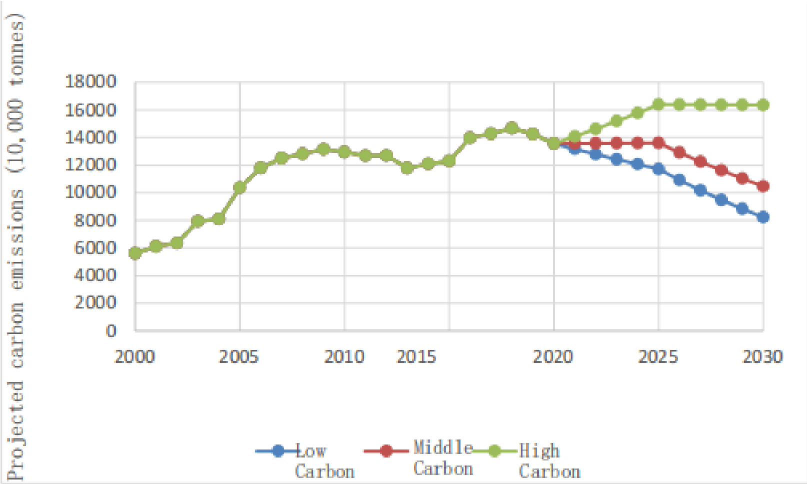

Figure 4: Trends of carbon emissions from energy consumption under three scenarios in Guangdong province from 2000 to 2030

Based on table 4, the population size, GDP per capita, industrial structure, energy consumption intensity and energy structure in the next 10 years are calculated, which are incorporated into the STIRPAT model formula, the prediction diagram in Figure 4 is obtained.

4. Summary

(1)The overall contribution of energy intensity to the carbon emission of energy consumption in Guangdong is negative, while the contribution of energy structure, industrial structure, per capita GDP and population is positive. (2)The contribution of carbon emission to energy consumption in Guangdong province is as follows: GDP per capita>energy intensity>population>energy structure >industrial structure. Through the analysis of the three scenarios of high, medium and low carbon, it is concluded that under the two scenarios of medium and low carbon, the carbon peak time of our country can be before 2030, while under the high carbon scenario, our country can not meet the carbon emission time ahead of schedule.

Although Guangdong faces great challenges in reducing emissions, there are still many favorable factors. For example: (1)New industrial technology advanced, so that it has higher energy efficiency and lower carbon emissions. (2)Adjustments can be made according to the actual situation. For example, in the southwest region, where hydropower is the main source, the “West-to-east power transmission” is an important clean energy source, while the liquefied natural gas industry is developing vigorously, is an effective way to reduce carbon dioxide emissions. (3)At present, the proportion of tertiary sector of the economy is on the rise. There is a lot of room for further development. Adjusting the industrial structure can also reduce carbon emissions.

Reducing emissions should focus on integrating energy-intensive industries, eliminating outdated capacity decisively, limiting high-carbon industries, supporting low-carbon industries, and allowing new energy-efficient technologies and processes to be rapidly transformed into productive forces. At the same time, "Green GDP" is included in the evaluation of its work efficiency, and its active monitoring.

Acknowledgement

Guangdong Province Science and Technology Innovation Strategy Special Fund Support, Project Name: Promoting Common Prosperity through the Development of Service Trade—— Based on text analysis and machine learning, project number: pdjh2023b0370

Qingyuan Philosophy and Social Sciences Project Funding, Project Number: QYSK2024082 Project Name: Research on the Implementation Path of Qingyuan's "Dual Carbon" Target Based on Fiscal Expenditure Structure and Tax Incentive Policies

ISSN 2706-6827 Vol. 6, Issue 9: 84-90, DOI: 10.25236/IJFS.2024.060913

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