Exploring the Carbon Footprint of Energy Consumption in Shanxi Province Based on the Tapio Decoupling and Grey BP Neural Network Model

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Abstract. This paper focuses on analyzing the carbon footprint of energy consumption in Shanxi Province, China. It utilizes data from sources such as the 'China Energy Statistical Yearbook' (2001-2022), the China Carbon Accounting Database (CEADs), and the 'Shanxi Statistical Yearbook' for an exploratory analysis of energy consumption and the province's economy. The study calculates the carbon footprint of energy consumption in Shanxi Province and employs the LMDI model to identify influencing factors. Additionally, it uses the Tapio decoupling model to assess the relationship between these factors and economic development. To forecast the carbon footprint from 2022 to 2026, a grey BP neural network prediction model is applied, demonstrating improved accuracy compared to BP and grey models, with MAE and RMSE values of 2.44 and 10.91.

Keywords: Energy Consumption, Carbon Footprint, LMDI Model, Tapio Decoupling Model, Grey BP Neural Network.

1. Introduction

1.1. Research Background and Significance

In 2022, China's National Development and Reform Commission and National Energy Administration issued guidelines for greening energy systems. They aim to boost green energy consumption, which will, in turn, drive the green and low-carbon transformation of energy production.

This research focuses on the carbon footprint, considering it as the amount of CO2 emissions[1]. It specifically investigates the energy consumption carbon footprint in Shanxi Province.

1.2. Research Objectives

Based on the above background, the purpose of this paper is to explore the current situation of energy consumption in Shanxi Province, China and measure the carbon footprint of energy consumption, including the following points:

1.Collect relevant data on energy consumption in Shanxi Province, conduct exploratory analysis, and calculate the carbon footprint of energy consumption over the past 21 years.

2.Analyze the influence of different industries in Shanxi Province on the carbon footprint of energy consumption. Conduct in-depth analysis and comparisons of the carbon footprint of energy consumption in the three major industries, identifying high carbon-emitting sectors and exploring factors affecting energy consumption carbon emissions in these sectors.

3. Investigate the relationship between Shanxi Province's energy consumption carbon footprint and its economic and social development, while analyzing correlations with key economic indicators, and provide sustainable development recommendations.

4.Forecast the future carbon footprint of energy consumption in Shanxi Province.

2. Calculation of Carbon Footprint of Energy Consumption in Shanxi Province

This paper assessed Shanxi Province's carbon footprint for energy consumption using 2017 Input-Output Table data, terminal energy consumption, and industry-specific data from the Shanxi

Statistical Yearbook. It segmented carbon footprints by energy type and industry, considering six energy sources: raw coal, washed coal, coke, petroleum products, electricity, and natural gas.

2.1. Calculation of Carbon Footprint of Industrial Energy Consumption in Shanxi Province

Following the guidelines of the Intergovernmental Panel on Climate Change (IPCC) for national greenhouse gas emission inventories, the carbon footprint calculation formula is derived as follows:

$$CE_t = \sum_i^6 E_{ti} \times S_i \times c_i \tag{1}$$

CE_t is the energy carbon footprint of year t, and the E_{ti} represents the consumption quantity of energy source i in year t; S_i is the carbon emission coefficient corresponding to each energy conversion standard coal and c_i its energy source, and the specific coefficient of energy conversion standard coal and carbon emissions is shown in Table 1.

Table 1. Table of Energy Conversion to Standard Coal and Carbon Emission Coefficients

Types of Energy Sources	Conversion Coefficient to Standard Coal	Carbon Emission Coefficient
Raw Coal	0.7143	0.7559
Washed and Other Cleaned Coal	0.6100	0.7559
Coke	0.9714	0.8550
Petroleum	1.4952	0.5857
Electricity	0.1229	0.2900
Natural Gas, Coal Gas, and Others	1.2127	0.4483

2.2. Results and Analysis of Carbon Footprint of Energy Consumption in the Three Major Industries of Shanxi Province

Through calculations, this paper has determined the carbon footprint of energy consumption (in ten thousand tons) for the three major industries in Shanxi Province, as shown in Table 2:

Table 2. Table of Carbon Footprint of Energy Consumption in the Three Major Industries

Year	Primary Industry	Secondary Industry	Tertiary Industry
2001	256.07	3624.11	410.28
2002	258.73	4347.07	439.35
2003	255.63	4879.19	480.15
2004	202.46	5149.74	580.44
2005	184.38	5543.87	677.69
2006	207.22	6209.28	734.79
2007	172.76	6520.34	764.05
2008	164.45	6658.52	1085.97
2009	249.45	6494.62	1578.59
2010	253.09	6807.80	1654.37
2011	256.67	7300.20	1656.40
2012	273.05	7641.77	1759.45
2013	283.23	7871.17	1820.29
2014	196.96	8291.17	1725.05
2015	196.46	7943.86	1846.91
2016	211.61	8020.24	1885.62
2017	214.36	8337.15	1966.37
2018	190.30	8253.89	1826.78
2019	194.27	8709.96	1891.79
2020	190.79	9261.14	1566.69
2021	191.88	9595.58	1575.46

Based on the above calculations to obtain the energy consumption carbon footprint data of the three major industries in Table 2, we conclude that the overall energy consumption carbon footprint of the primary industry shows a downward trend, with a change of about -25% from 2001 to 2021. This may be due to the increased efficiency of energy consumption in the primary sector. The overall carbon footprint of energy consumption in the secondary sector is on the rise, with a change of about 165% from 2001 to 2021. This shows that with the rapid development of the secondary industry in Shanxi Province, its energy consumption is also increasing. Between 2015 and 2020, energy consumption in the secondary sector showed a slight decline or even fluctuated, possibly due to stricter environmental policies in Shanxi Province. The carbon footprint of energy consumption in the tertiary sector has increased overall, with a change of about 284% from 2001 to 2021. This may be due to the fact that with the economic transformation and service industry development in Shanxi Province, the demand for energy in the tertiary industry is also increasing.

3. Measurement and analysis of carbon footprint of energy consumption in different industries in Shanxi Province

3.1. Based on the IPCC inventory guidelines combined with the input-output method to measure the carbon footprint of energy consumption

The regional input-output table for Shanxi Province is compiled every five years [2]. This paper utilizes the most recent data from the 2017 input-output table for Shanxi Province.

$$X_i = \sum_{j=1}^{n} x_{ij} + Y_i \tag{2}$$

X_i represents the total output of the i sector in Shanxi Province, and x_{ij} represents the intermediate input from sector i to sector j. Y_i represents the final demand for products from the i sector. This information is used to construct the total output matrix X:

$$X = (I - A)^{-1} W \tag{3}$$

Calculate the direct carbon emission coefficient matrix T:

$$T = \frac{\sum_{i=1}^{n} E_{ij} \times M_j \times V_j \times C_j \times O_j}{x_j} \tag{4}$$

E_{ij} represents the energy consumption value of the i industry for the j type of energy, M_j is the standard coal conversion coefficient for energy type j, V_j is the average lower heating value of energy j, C_j is the carbon content per unit heat, O_j is the oxidation rate of energy j, and x_j is the total output of sector j.By integrating carbon footprint calculations with input-output modeling and introducing carbon emission coefficients, we can calculate the carbon emissions. Ultimately, we can obtain the sector-specific carbon footprint C as follows:

$$C = T(I - A)^{-1} W \tag{5}$$

4. Analysis of Factors Influencing the Carbon Footprint of Energy Consumption in Shanxi Province

4.1. Selection of Factors and Indicators for Influencing Factors of Energy Consumption Carbon Footprint

To better analyze the factors influencing Shanxi Province's carbon footprint, we divided the period from 2001 to 2021 into seven time periods based on the characteristics of carbon footprint changes. This division of time periods can provide a clearer picture of the patterns and trends in carbon footprints, allowing us to analyze the mechanisms and effects of various carbon footprint influencing factors in each period.

Building on existing research, with regard to the factors influencing the carbon footprint of energy consumption in Shanxi Province, we have categorized the influencing factors into CI、ES、EI、SI、G、PA, and US. The specific meanings of each indicator are shown in Table 3.

Table 3. Table of Variable Descriptions

Variable	Name	Implication	Type
ES	Energy Structure	The consumption of the j type of energy in the i industry./ The total consumption of all types of energy in the i industry.	Energy Indicators
EI	Energy Intensity	The total consumption of various types of energy in the i industry./ The gross output value of the i industry.	Energy Metrics
SI	Industrial Structure	The gross output value of the i industry./ Regional GDP	Industrial Indicators
G	Economic Factors	Regional GDP / Total population	Economic Metrics
PA	Population Density	Total population / Urban built-up area	Population Metrics
US	Urban Scale	Urban built-up area	Urban Development Indicators

4.2. Exploring Carbon Footprint Influencing Factors Using the LMDI Model

LMDI (Logarithmic Mean Divisia Index) is a decomposition model that provides a detailed analysis of changes in energy consumption and carbon footprint by decomposing data. In this study, we focus on the influencing factors of energy consumption carbon footprint in Shanxi Province and, considering the practical situation, use the LMDI model for factor decomposition. The specific model is as follows:

$$\begin{aligned} C &= \sum_{ij} \frac{C_{ij}}{E_{ij}} \cdot \frac{E_{ij}}{E_i} \cdot \frac{E_i}{G_i} \cdot \frac{G_i}{G_{GDP}} \cdot \frac{G_{GDP}}{P} \cdot \frac{P}{BA} \cdot BA \\ &= CI + ES + EI + SI + G + PA + US \end{aligned} \tag{6}$$

Where C represents the carbon footprint, i=1,2,3 represents the first industry, the second industry, and the third industry, respectively, and $j = 1,2, \ldots, 6$ represents the six main fossil fuel types, including raw coal, washed coking coal and other washed coal, coke, petroleum, electricity, and natural gas coal gas, etc. E_{ij} represents the consumption of the j type of energy in the i industry, E_i represents the total consumption of various types of energy in the i-th industry, G_i is the gross output value of the i industry, G_{GDP} represents the regional GDP, Prepresents the total population, and BA represents the built-up area.

Using the LMDI decomposition model, the change in the carbon footprint can be decomposed into 7 indicators. The decomposition formula is as follows:

$$\Delta C = C_t - C_0 = \Delta CI + \Delta ES + \Delta EI + \Delta SI + \Delta G + \Delta PA + \Delta US \tag{7}$$

ΔC represents the change in carbon footprint from year 0 to year t; C_t represents the carbon footprint in the target year; C_0 represents the carbon footprint in the base year; ΔCI、ΔES、ΔEI、ΔSI、ΔG、ΔPA、and ΔUS respectively represent the changes in carbon intensity effect, energy structure effect, energy intensity effect, industrial structure effect, economic factor effect, population density effect, and urban scale effect. ΔES can be expressed using the following formula:

$$\Delta ES = \sum_{ij} \frac{C_{ijt} - C_{ij0}}{lnC_{ijt} - lnC_{ij0}} ln \frac{ES_{ijt}}{ES_{ij0}} \tag{8}$$

which can meet the demand completely, and has fast prediction speed and convenient operation. The expressions for the other effects are similar to ΔES However, in this study, because constant energy carbon emission coefficients are used, ΔCI is either ignored or treated as 0 in the model.

The contribution rate is used to intuitively reflect the impact of various factors on the carbon footprint of Shanxi Province. It provides a more direct way to show the direction and magnitude of the effects of each factor, further revealing the reasons for the changes in Shanxi Province's carbon footprint. In this paper, α_{ES}、α_{EI}、α_{SI}、α_{G}、α_{PA}, and α_{US} are used to represent the contribution rates of energy structure, energy intensity, industrial structure, economic growth, population density, and urban scale to the changes in the carbon footprint. Taking α_{ES} as an example:

$$\alpha_{ES} = \frac{\Delta ES}{\Delta C} \tag{9}$$

The calculation formulas for α_{EI}、α_{SI}、α_{G}、α_{PA} and α_{US} are similar to α_{ES}, and the sum of these six factors equals 1. The calculation results are shown in Table 4 as follows:

Table 4. The contribution rates of each factor.

Year	α_{ES}	α_{EI}	α_{SI}	α_{G}	α_{PA}	α_{US}
2001-2003	0.00	-1.61	-2.20	3.31	0.90	0.60
2004-2006	0.27	-0.16	0.13	0.26	0.43	0.08
2007-2009	0.53	0.13	0.80	-0.33	-0.01	-0.11
2010-2012	-0.08	-0.35	0.21	0.68	0.12	0.42
2013-2015	0.08	0.27	0.24	-0.02	0.25	0.18
2016-2018	-0.03	0.40	0.49	0.20	-0.07	0.01
2019-2021	-0.01	0.35	0.38	0.20	0.06	0.03

From Table 5, the impact of economic growth on carbon footprint gradually decreases with time, and in the six growth rates, the impact of energy intensity, economic factors, population density and city size on the carbon footprint of Shanxi Province is decreasing, and over time, Shanxi Province began to increase the supervision and governance of carbon emissions, and with the gradual popularization and promotion of clean energy, the proportion of traditional energy such as coal in the energy structure gradually decreased, which increased the impact of the energy structure on the carbon footprint.

4.3. Analysis of the Decoupling Relationship Between Energy Consumption Carbon Footprint and Economic Growth Based on the Tapio Decoupling Model

4.3.1 Build a Tapio decoupling model

Building a decoupling model between energy consumption carbon footprint and energy consumption in Shanxi Province based on the Tapio decoupling theory. The calculated energy consumption carbon footprint of Shanxi Province, estimated from data, is introduced into the Tapio decoupling model [3] to calculate the decoupling relationship between energy consumption carbon footprint and economic development in Shanxi Province.

The formula for calculating the decoupling elasticity coefficient between energy consumption carbon footprint and economic growth in Shanxi Province is as follows:

$$I_{\mathrm{t}} = \frac{\Delta C/C_0}{\Delta GDP/GDP_o} \tag{10}$$

In the above formula, I_{t} refers to the elastic coefficient of decoupling in the t year, ΔC is the change in carbon footprint between the target year and the base year, C_0 is the carbon footprint of the base year, ΔGDP is the change in GDP between the target year and the base year, and GDP_o is the GDP of the base year.[4] The specific measures of the decoupling index are shown in Table 5 below:

Table 5. Decoupling Index Standard Table

Carbon Footprint Change Rate	Economic Growth Change Rate	I_t	Decoupling Status	Symbol
≤ 0	>0	$I_t \leq 0$	Strong Decoupling	1
>0	>0	$0<I_t<0.8$	Weak Decoupling	2
<0	<0	$I_t>1.2$	Recessionary Decoupling	3
<0	<0	$0 \leq I_t<0.8$	Weak Negative Decoupling	4
≥ 0	<0	$I_t \leq 0$	Strong Negative Decoupling	5
>0	>0	$I_t>1.2$	Expansive Negative Decoupling	6
<0	<0	$0.8 \leq I_t \leq 1.2$	Recessionary Coupling	7
>0	>0	$0.8 \leq I_t \leq 1.2$	Expansive Coupling	8

Among them, decoupling includes three states: strong decoupling, weak decoupling, and recession decoupling; Negative decoupling includes three states: weak negative decoupling, strong negative decoupling, and extended negative decoupling; Connections include two states: recession connection and expansion connection.

4.3.2 Analysis of decoupling of carbon footprint of energy consumption and economic growth in various industries in Shanxi

The calculation formula yields the decoupling elasticity values between energy consumption carbon footprints and economic growth for the three major industries in Shanxi Province, as shown in Table 7 for their decoupling status.

Table 6. The decoupling of the carbon footprint of energy consumption and economic growth in the three major industries

Year	Primary Industry	Secondary Industry	Tertiary Industry
2001-2003	1	2	2
2004-2006	5	2	2
2007-2009	8	1	6
2010-2012	2	2	2
2013-2015	1	5	5
2016-2018	1	2	1
2019-2021	1	2	1

As can be seen from Table 6, the decoupling status of the three major industries is more complicated, and the relationship between them varies from year to year. The decoupling status of the primary industry in different years has changed greatly, including strong decoupling and expansion connection, as well as strong negative decoupling, indicating that the impact of agriculture on economic growth and the implementation of environmental protection measures is very significant. The decoupling state of the secondary industry is relatively weak for most of the time, showing a high relationship between carbon emissions and economic growth. From 2013 to 2015, the secondary industry experienced a strong decoupling, which may be related to the domestic policy of vigorously promoting energy conservation and emission reduction. The tertiary sector has shown a state of weak decoupling and expansion for most of the time, which shows that more efforts are still needed to achieve a benign interaction between economic growth and the implementation of environmental protection measures.

4.3.3 Analysis of factors affecting decoupling relationship

To further analyze the role of each influencing factor in the decoupling relationship, this paper combines LMDI decomposition with the Tapio decoupling model [5] to create an extended decoupling model, with the following formula:

$$\begin{aligned} I_{\mathrm{t}} &= \frac{\Delta C/C_0}{\Delta GDP/GDP_o} = \Delta C \cdot \left(\frac{GDP_0}{\frac{\Delta GDP}{C_0}}\right) \\ &= \Delta ES \cdot \left(\frac{GDP_0}{\frac{\Delta GDP}{C_0}}\right) + \Delta EI \cdot \left(\frac{GDP_0}{\frac{\Delta GDP}{C_0}}\right) + \Delta SI \cdot \left(\frac{GDP_0}{\frac{\Delta GDP}{C_0}}\right) \\ &\quad + \Delta G \cdot \left(\frac{GDP_0}{\frac{\Delta GDP}{C_0}}\right) + \Delta PA \cdot \left(\frac{GDP_0}{\frac{\Delta GDP}{C_0}}\right) + \Delta US \cdot \left(\frac{GDP_0}{\frac{\Delta GDP}{C_0}}\right) \\ &= I_{ES} + I_{EI} + I_{SI} + I_G + I_{PA} + I_{US} \end{aligned} \tag{11}$$

In the formula, I_{ES}, I_{EI}, I_{SI}, I_G, I_{PA}, and I_{US} are the six sub-indices of I_{t}, representing the decoupling elasticity coefficients for energy structure, energy intensity, industrial structure, economic factors, population density, and urban scale [6].

Using the formula, the decoupling elasticity coefficients for energy structure, energy intensity, industrial structure, economic factors, population density, and urban scale were decomposed for the energy consumption carbon footprint in Shanxi Province, as shown in Table 7 [7].

Table 7. Decomposition of decoupling factors from energy consumption carbon footprint and economic growth in Shanxi Province

Year	I_{ES}	I_{EI}	I_{SI}	I_G	I_{PA}	I_{US}	I_{t}
2001-2003	-0.0003	-0.3989	-0.5442	0.8205	0.2222	0.1484	-0.0003
2004-2006	0.8145	-0.4864	0.3900	0.8071	1.3024	0.2355	0.8145
2007-2009	-1.3195	-0.3313	-1.9868	0.8274	0.0274	0.2866	-1.3195
2010-2012	-0.0916	-0.4020	0.2366	0.7804	0.1420	0.4844	-0.0916
2013-2015	-2.4880	-8.2540	-7.1864	0.5380	-7.5310	-5.4409	-2.4880
2016-2018	-0.1257	1.5536	1.8947	0.7916	-0.2879	0.0520	-0.1257
2019-2021	-0.0537	1.3784	1.5029	0.8152	0.2439	0.1038	-0.0537

As can be seen from Table 8, The decoupling elasticity index of economic effects was greater than 0.80 from 2001 to 2009, indicating that per capita GDP significantly affected the decoupling of Shanxi's energy consumption carbon footprint from economic growth, and GDP growth at the cost of high carbon will continue to damage the sustainable development of ecology; the city-scale elastic decoupling index was only negative from 2013 to 2015, and the rest were positive, and the decoupling elasticity index continued to grow as a whole. The urban scale chosen in this paper is from the perspective of land expansion, which shows that the continuous expansion of built-up land uses generates a large amount of carbon emissions. The growth of built-up areas should be properly controlled, as reasonable land expansion can reduce the carbon footprint while keeping the city growing; The decoupling resilience index for energy intensity effects was positive from 2016 to 2021, while the remaining years were negative. Therefore, optimizing energy intensity will help reduce the carbon footprint and maintain high economic growth; The decoupling elasticity index of energy structure effect is small, only positive in 2004-2006, and the decoupling impact on the carbon footprint of energy consumption and economic growth in Shanxi Province is small.

5. An analysis of future carbon footprint predictions in Shanxi Province in the context of green transformation.

5.1. Gray BP neural network model construction

Many scholars use Grey GM(1,1) and BP (Backpropagation) neural network models for predicting carbon emissions. Grey GM(1,1) excels in small-sample forecasting, providing objective conclusions. However, it's suitable for short to medium-term predictions. BP neural networks handle nonlinear relationships well, making them ideal for predicting energy consumption carbon footprints.This paper adopts a Grey BP Neural Network [8], combining Grey Model's precision in short-term forecasting with BP neural network's strong learning and nonlinear optimization abilities. This fusion enhances accuracy and stability, especially with limited data, resulting in more precise predictions.

5.2. Analysis of carbon footprint prediction results of energy consumption in Shanxi Province

In this paper, the forecasting data from the Grey Forecasting Model, BP Neural Network Model, and Grey BP Neural Network Model are compared with the actual data, and the accuracy and precision of the models are calculated[9]. After obtaining the forecasting results of the models, a comparison is made among the Grey Forecasting Model (Grey), BP Neural Network Model (BP), and Grey BP Neural Network Model (Grey BP), as shown in Table 8.

Table 8. Comparison of Three Prediction Models

Year	Actual Value	Grey Forecast Value	Grey Forecast Error	BP Forecast Value	BP Forecast Error	Grey BP Forecast Value	Grey BP Forecast Error
2019	8928	9392	5.196	9135	2.32	8866	0.69
2020	9104	9612	5.578	9328	2.46	9015	0.011
2021	9402	9834	4.594	9588	1.98	9311	0.98

Through the initial error analysis of actual values and error values, it can be seen that the Grey BP Neural Network exhibits smaller prediction errors. The model accuracy is tested using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), and the Grey BP Neural Network demonstrates higher precision and accuracy in predicting energy consumption carbon footprints [10]. This can provide valuable reference recommendations for future energy consumption policies and control of energy consumption carbon footprints in Shanxi Province, as shown in Table 9.

Table 9. Accuracy of Three Prediction Models

Prediction Models	MAE	RMSE
Grey Model	418.05	524.55
BP Neural Network Model	13.5	60.62
Grey BP Neural Network Model	2.44	10.91

In conclusion, the use of the Grey BP Neural Network Model for predicting energy consumption carbon footprints results in a significant reduction in errors compared to both the Grey Model and BP Neural Network Model. It exhibits higher precision and better accuracy. Therefore, for forecasting energy consumption carbon footprints in Shanxi Province, the Grey BP Neural Network Model can be employed. Based on the Grey BP Neural Network Model, the future five-year energy consumption carbon footprints are presented in Table 10.

Table 10. Energy Consumption Carbon Footprint Forecast Table for 2022-2026

Time (Year)	2022	2023	2024	2025	2026
Carbon Footprint Forecast Value	9967	10559	11057	11416	11694

Regarding the future five-year energy consumption carbon footprint forecast values for Shanxi Province in the table, it can be observed that the forecasted values continue to show an upward trend. However, the rate of increase is steadily decreasing, indicating that there may be a point in the future where the energy consumption carbon footprint reaches its peak. Nevertheless, achieving the "dual carbon" goals still presents certain challenges.

6. Conclusion

This paper analyzed the economic development and energy situation in Shanxi Province. It was found that the economic development is relatively fast, the GDP of the tertiary industry is continuously increasing, and the industrial structure is becoming more reasonable. However, energy consumption continues to grow, indicating that Shanxi Province still faces challenges in achieving the "dual carbon" goals, with rising energy consumption and difficulties in energy transition. Using the Tapio model, it was determined that economic growth and industrial structure are the main factors affecting the carbon footprint change in Shanxi Province. Energy intensity and energy structure have a dual role in affecting the carbon footprint, with energy intensity making a significant negative contribution. Population agglomeration has a critical point in its impact on the carbon footprint. Before reaching the critical point, population agglomeration exhibits diminishing marginal effects, while it transitions to a promoting effect after surpassing the critical point.There is a close association between energy consumption carbon footprint and economic growth in Shanxi Province, and the development of economic effects can reduce the dependency of Shanxi Province's economic growth on energy consumption. The trend of increasing energy consumption carbon footprint in Shanxi Province is steadily decreasing, leaving greater room for the transformation of its resource-based economy in the future.

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