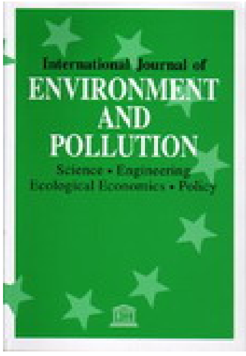

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Evaluation and trend prediction of the relationship between carbon emissions, energy, and sustainable growth based on neural networks

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Evaluation and trend prediction of the relationship between carbon emissions, energy, and sustainable growth based on neural networks

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Abstract: This study investigates the relationship between carbon emissions (CE), energy, and sustainable growth using neural networks. Data from five regions – North America, South America, Europe, Asia Pacific, and Africa – were analysed to model CE trends based on energy structure and consumption. A neural network model was trained and optimised to predict correlations among CE, energy use, and economic growth. Focusing on China, the study examines vehicle emissions, fuel-powered versus new energy vehicle sales, and their impact on CE and the economy. Results show a strong correlation between energy consumption and CE ($R = 0.99$), with energy efficiency and composition also influencing emissions. As new energy vehicle adoption rises, fossil fuel demand declines, helping curb total CE, support carbon neutrality, and promote sustainable development. The model demonstrates that optimising energy structure is key to balancing economic growth and environmental protection.

Keywords: carbon emissions; neural networks; energy mix; energy consumption; data analysis; sustainable development; climate change.

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1 Introduction

In the context of today's world economy, all countries have taken the development of low-carbon economy as their development direction. China is the second largest energy consumer in the world after the USA, and its carbon dioxide emissions exceed those of the USA, ranking first in the world. At present and in the future, economic growth would face both energy issues and international pressure to reduce carbon dioxide emissions (Li et al., 2023). In this context, how to achieve a balance between energy consumption, CE, and economic growth has become a focus of attention for countries around the world today. The Paris Agreement requires keeping the temperature rise within 2°C, and encourages countries to optimise their energy structure and develop low-carbon technologies. China is facing the pressure of emission reduction and growth, and urgently needs to improve energy efficiency and structural transformation, which highlights the application value of the neural network prediction model in this study.

Energy has played a significant supporting role in various aspects of human economic life. With the development of human society, energy has played an increasingly important role in the development of the national economy (Lv et al., 2020, 2021). In the context of economic globalisation, the economic development speed of many regions is very fast, and people's living standards have also been greatly improved. However, in this process, a large number of problems such as energy consumption, environmental pollution, and ecological damage have also emerged. Especially, fossil fuels play an important role in energy consumption in many regions, accounting for over half of the total energy consumption (Huang and Rudolph, 2021; Huang et al., 2022). Due to the one-time depletion and non-renewable nature of fossil fuels, excessive development would ultimately lead to their depletion. In many countries, energy and environmental issues have become increasingly prominent constraints and to some extent affect the long-term development of the economy (Xiao et al., 2022; Lou et al., 2023). Therefore, in order to achieve sustainable development, it is necessary to spare no effort to solve the primary issue of energy, and whether sustainable economic and social development can be achieved has become a top priority.

This paper used neural networks to analyse the relationship and trend of CE, energy, and sustainable growth, and conducted literature review to extract effective experience. After collecting a large amount of relevant data on CE, energy efficiency consumption, and energy structure in five regions of North America, South America, Europe, Asia Pacific, and Africa, a neural networks prediction model was studied and optimised using software. The results showed that energy consumption and economic growth belonged to a causal relationship, and there was a correlation between economic development and CE. The innovation of this paper lies in the construction of a back propagation (BP) neural network model to quantitatively analyse the cross-regional dynamic relationship between carbon emissions, energy structure and economic growth. It integrates multi-dimensional data from five continents for the first time, reveals the high correlation between energy consumption and carbon emissions, and provides a data-driven forecasting tool for low-carbon policies.

2 Related work on literature review

With the rapid development of the economy, it is of great significance to coordinate the relationship between energy, economy, and CE. Danish et al. (2020) used empirical results to confirm the positive role of environmental regulations in reducing CE. Taner (2019) estimated that renewable energy had positive and statistical significance for the sustainable development of both developed and developing countries based on the results of multi energy CE research. Buhari et al.'s (2021) research attempted to analyse the impact of economic complexity on CE, which was understood as a structural transformation towards more complex and knowledge-based production, economic progress, renewable energy consumption, and population growth. Imran (2018) studied the impact of economic growth, urban expansion and the consumption of fossil fuels, solid fuels and renewable energy on environmental degradation of developing economies in sub Saharan Africa. Umer and Ranjan's (2020) research aimed to identify the causal relationship between energy consumption, gross domestic product growth, and carbon dioxide emissions in Brazil, Russia, India, China, and South Africa between 1990 and 2017. Zhao et al. (2021) believed that in the face of the COVID-19, the interaction between regional economic growth, energy consumption and CO_2 emissions was a key issue for China to continue to promote ecological civilisation and achieve green and sustainable development. Many studies have shown a long-term equilibrium relationship and a short-term dynamic adjustment mechanism between CE, energy, and sustainable growth. Existing research often focuses on the isolated impact of a single factor on carbon emissions and lacks multi-dimensional dynamic correlation analysis; there is insufficient exploration of the application of emerging technologies in cross-regional forecasting; and regional coverage is uneven, resulting in weak empirical support for policy recommendations.

How to calculate and predict CE and total energy consumption is an important topic in the current neural networks prediction and warning system. Oveis et al.'s (2018) research content was that the prediction of solar power generation involved the understanding of the sun, atmosphere and other parameters, as well as the scattering process and specifications of solar power station using solar energy for power generation. This prediction result was crucial to the effective utilisation of solar power station, grid management and solar energy trading. A new prediction method based on the combination of neural networks and meta heuristic algorithm was proposed as a hybrid prediction engine. Elham et al. (2020) believed that energy management and reducing carbon dioxide emissions increased research on energy input-output analysis, especially in the agricultural sector. The main purpose of the study was to evaluate the energy use mode and select the best method of neural networks to estimate the output energy of Jiroft City in the south of Kerman Province, Iran. Rezaei et al. (2018) used the type of fuel and its share in the total consumption of primary energy as the indicator of economic activity gross domestic product and the share of renewable energy, which played a key role in carbon dioxide emissions, and observed that the maximum absolute error of using GMDH (Group Method of Data Handling) artificial neural networks was less than 4% (Mohammad et al., 2018). The above research indicates that the BP neural networks model for predicting CE can greatly improve the training speed of the neural networks and achieve good prediction results.

3 Neural networks evaluation methods

3.1 Data collection and preprocessing

Before collecting and preprocessing data on CE, this paper conducted background research on CE. The main manifestation is that global warming poses a huge threat to human survival and development as global temperatures rise, sea levels rise, glaciers melt, and low-lying islands disappear. This is mainly because with the development of human society, the large-scale combustion of minerals such as oil, natural gas, and coal has generated a large amount of CO_2. In order to mitigate climate change and slow down Earth's surface warming, it is necessary to continuously reduce CO_2 emissions. Therefore CO_2 emission reduction is currently a global concern.

According to a United Nations report, the concentration of CO_2 in the global atmosphere before the Industrial Revolution was 280 ppm. By 2012, the concentration of CO_2 had risen to 393.1 ppm. In order to avoid global glacier melting and extreme weather conditions, the current global temperature rise cannot exceed 2 degrees Celsius. If the current trend of using fossil fuels continues, it is predicted that the global concentration of CO_2 would reach 700 ppm, which would lead to an increase in global temperature of 1.4–4.8 degrees Celsius, causing irreversible consequences.

This paper selects five regions, North America, South America, Europe, Asia Pacific and Africa, as the target subjects for data collection. The CE inventory has always been an important basis for building climate model, formulating national emission reduction policies, and international negotiations and games (Muhammad et al., 2020). The compilation of national CE inventories often involves accounting for the greenhouse gases emitted or absorbed by human activities on a national basis.

3.1.1 Data organisation of CE

With the development of the global economy, the per capita emissions of CE have significantly increased. CE in various countries around the world has increased with economic growth. However, in recent years, there have been signs of a slowdown in the growth rate. With the development of the economy, the demand for energy such as electricity and oil in various sectors has also increased, and the production of electricity and the utilisation of fossil fuels such as oil and natural gas would bring about a large amount of CE (Li et al., 2013, 2015; Yu et al., 2022). Here are statistical tables of CE from various regions collected:

Table 1 summarises the CE of the five regions of North America, South America, Europe, Asia Pacific, and Africa from 2015 to 2021. It was evident that the total CE of the Asia Pacific region were much higher than those of other regions, with a cumulative total of 117,248 kg of CE for the seven years to 2021, which was more than the seven year total of the other four regions. The reason for this was related to the economic development plan of the Asia Pacific region. Among the five regions mentioned above, South America had the lowest total CE in 7 years, with an overall reduction of 135 kg compared to Africa; the total annual CE in North America decreased by approximately 6% from 2015 to 2021, while the total annual CE in Europe decreased by approximately 7% from 2015 to 2021. The total annual CE in the Asia Pacific region increased by approximately 12% from 2015 to 2021.

Table 1 Statistical table of CE by region (kg)

	North America	*South America*	*Europe*	*Africa*	*Asia-pacific*
2015	6130	1150	4270	1160	15,850
2016	5980	1230	4255	1185	16,130
2017	5950	1210	4215	1120	16,355
2018	6240	1190	4180	1175	17,055
2019	6050	1140	4130	1165	17,350
2020	5260	1030	3755	1160	16,753
2021	5750	1020	3950	1140	17,755
Total	41,360	7970	28,755	8105	117,248

3.1.2 Data organisation of energy structure and consumption

In the process of sorting out the data of energy structure and consumption, this paper found that the current increasing energy crisis has made people pay more and more attention to energy issues, and it is also a hot topic of the trend of world energy resources structure. In terms of regional composition, the three regions of North America, Europe and the Asia Pacific region are the main consumers of primary energy (Fang et al., 2023; Ran et al., 2024). Since 2000, the Asia Pacific region has surpassed North America, becoming the largest consumer of primary energy in the world and is still growing. However, primary energy consumption in major developed countries is decreasing, and large-scale investments have been made in clean energy in the context of increasing attention from countries around the world. However, the growth rate of investment in traditional fossil fuels has slowed down or even experienced negative growth. In the future, the proportion of fossil fuels would gradually decrease, and this market share would be transferred to clean energy sources such as hydropower and renewable energy (Salman et al., 2022; Yao et al., 2023). Here, the energy consumption structure statistics of the above five regions are summarised, as shown in Table 2.

Table 2 Statistical table of energy consumption structure

	North America	*South America*	*Europe*	*Asia-Pacific*	*Africa*
Coal	15.4	5.1	15	47.5	22
Petroleum	39.3	42.4	36.2	28.3	41.5
Natural gas	31	19.8	23	11.9	27.4
Hydroenergy	5.7	20.4	7.1	6.4	6.5
Wind energy source	4.2	5	8.4	3.8	1.6
Nuclear energy	4.4	7.3	10.3	2.1	1

Table 2 summarises the energy consumption structure of the five major regions, with the main energy consumption being coal, oil, natural gas, hydropower, wind energy, and nuclear energy. Among them, the energy consumption structure in North America is mainly composed of oil and natural gas, supplemented by coal; the energy consumption structure in South America is mainly composed of oil and hydropower, supplemented by natural gas; the energy consumption structure in Europe is mainly composed of oil and natural gas, supplemented by coal and nuclear energy; the energy consumption structure in the Asia Pacific region is mainly composed of coal and oil, supplemented by natural gas; the energy consumption structure in Africa is mainly characterised by oil and natural gas, supplemented by coal. Among the above five regions, the region with the highest coal energy consumption is Asia Pacific, and the region with the highest oil energy consumption is South America. The region with the highest natural gas energy consumption is North America, and the region with the highest water energy consumption is South America. The region with the highest consumption of wind and nuclear energy is Europe.

The purpose of the energy consumption structure statistics here is to demonstrate that energy plays a crucial role in the world's development process. It drives the great wheel of human history forward continuously, is a key factor in maintaining the normal operation of all industrial sectors, and is also an indispensable basic material in human daily life (Karmah, 2023; Guo, 2022). The scarcity of energy would have a direct impact on the normal production and living activities of a country. Among all types of energy, fossil energy is a dominant energy source that has been developing since the early stages of industry until now. It has made tremendous contributions to human industrialisation and modernisation (Hamzah, 2018; Wang et al., 2024). In a sense, fossil energy is not only the engine of a country's economic development, but also an important driving force for its development. On the other hand, the further exploitation and use of fossil energy, as well as the consumption of fossil energy, also benefit from economic development. However, while fossil energy consumption promotes a country's economic growth, it also brings a series of serious problems to a country.

At the same time, a major result of the combustion and utilisation of fossil fuels is their emissions of greenhouse gases (Muhammad and Narayan, 2021; Chen et al., 2024). Under the accumulation of these gases, the global ecological environment has been severely damaged, and the disasters caused by climate change caused by climate change every year have brought huge economic losses to humanity. Therefore, global warming and abrupt climate change have become a global problem. No country can avoid and must face this issue squarely. It is in the context of this climate crisis that various regions have proposed the development of a low-carbon economy of energy conservation and emission reduction and pointed out the direction of future economic development of various countries. The main method currently is to optimise its energy structure. Here is a summary of the energy structure of the five regions mentioned above, as shown in Table 3.

Table 3 Energy structure analysis

	Fossil energy structure	*Clean energy structure*	*Renewable energy structure*
North America	82.4	58.9	9.9
South America	70.7	50	28.6
Europe	74.2	48.8	15.5
Asia-Pacific	87.6	24.2	10.3
Africa	91.4	36.6	8.1

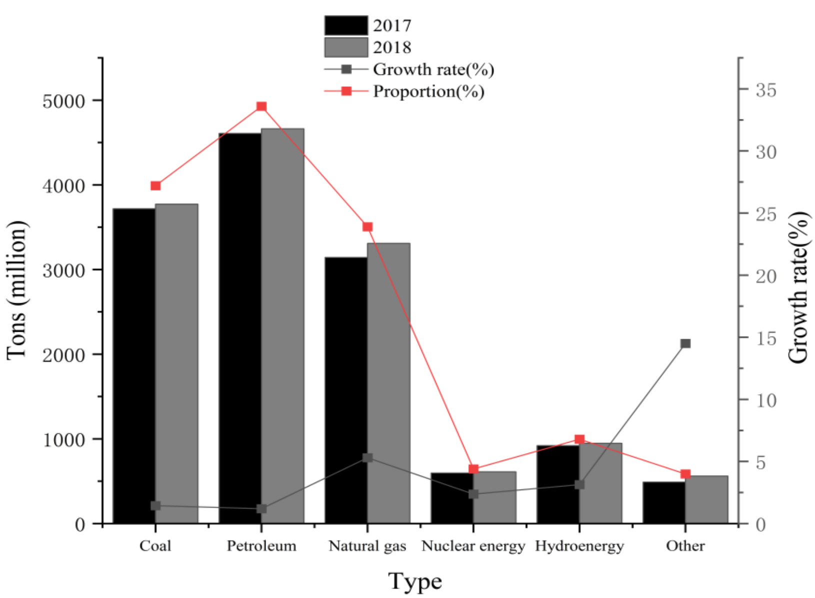
Table 3 mainly divides the energy structure of each region into three parts, among which the fossil energy structure includes coal, oil, and natural gas; clean energy includes nuclear energy, hydropower, wind energy, solar energy, natural gas, etc.; renewable energy includes hydropower, wind energy, solar energy, etc.

Africa's low energy efficiency is mainly constrained by weak infrastructure, backward technology and insufficient investment. Data shows that fossil energy accounts for as high as 91.4% of its energy structure, clean energy accounts for only 36.6%, and the utilisation rate of renewable energy such as hydropower and wind power is insufficient. Inefficient coal and oil consumption patterns increase carbon emissions, while low energy access rates (such as less than 50% grid coverage in rural areas) further limit economic potential. Africa needs to optimise its energy structure through international technology transfer, give priority to the development of local clean energy such as solar energy and biomass energy, and establish an energy efficiency improvement subsidy mechanism to balance emission reduction targets with economic growth needs.

It can be seen from the table that the energy structure in most regions of the world is still dominated by fossil fuels. In order to provide a more detailed and specific analysis of the energy structure, this paper analysed the total consumption, growth rates, and ratios of coal, oil, natural gas, nuclear energy, hydropower, and other energy sources worldwide in 2017 and 2018, as shown in Figure 1.

Coal is a solid fossil fuel with low combustion efficiency and high pollution, and is mainly used for power generation and heavy industry; oil is a liquid energy source, which is refined into gasoline and diesel, and dominates the transportation sector; natural gas is a gaseous clean energy source with lower carbon emissions than the first two, and is often used for power generation, heating and chemical industry. The carbon intensity of the three is decreasing, and the optimisation of energy structure requires gradually replacing coal and increasing the proportion of natural gas and renewable energy.

Figure 1 Global primary energy consumption structure (see online version for colours)



The *x*-axis in Figure 1 represents the energy type. The left y-axis represents the total energy consumption, while the right y-axis represents the proportion. The legends are for 2017, 2018, as well as growth rates and ratios. It could be seen from the graph that the total consumption of coal, oil, natural gas, nuclear energy, hydropower, and other energy sources in 2018 increased compared to 2017. The energy proportion line clearly showed its trend and changes with the total energy consumption. Among them, coal, oil and natural gas accounted for a relatively high proportion.

In summary, the proportion of fossil fuels would gradually decrease in the future, and this market share would be transferred to clean energy sources such as hydropower and renewable energy. At the same time, the energy production and consumption structure dominated by coal has also brought a series of problems. The energy efficiency of coal is far lower than that of oil and natural gas, so using coal as a pillar energy can cause serious environmental pollution, which not only makes environmental problems more severe, but also affects the global climate. The long-term, large-scale, and high-density development of coal resources has led to increasingly serious ecological problems (Malayaranjan, 2021).

3.1.3 Data organisation for sustainable economic growth

This paper believes that in order to achieve sustainable economic growth, it is necessary to have a good ecological environment and active participation of people in their own development decisions. Among them, environment and society are important indicators for measuring economic and environmental sustainable development. It is necessary to utilise resources reasonably, efficiently, and economically without damaging the ecological environment. In terms of the environment, it needs to avoid economic development at the cost of environmental degradation. It is not only needs to control environmental pollution, but also to improve environmental quality. At the same time, it is necessary to maintain the integrity of the Earth’s ecology, so that human development is always within the carrying capacity of the Earth.

This paper used data from China from 2015 to 2020 as the research sample and selected China’s gross domestic product as the expected output variable. The variable data is adjusted by the deflator index; CE are considered as non-expected output variables, with labour and coal energy as input variables. Due to the lack of clear statistical criteria for the labour force population, the labour force variable used here is the number of employees in the country over the years, as shown in Table 4.

Table 4 Statistics of china’s CE and economic development indicators from 2015 to 2020

	Carbon emissions (100 million tons)	*Gross national product (trillion yuan)*	*Coal energy (10000 tons)*	*Labour force (10000 people)*
2015	10.48	11.06	375,000	78,633.9
2016	10.95	11.23	341,000	78,699.6
2017	11.35	12.31	352,000	78,718.3
2018	11.77	13.89	367,575	78,598.6
2019	12.09	14.28	386,075	78,398.1
2020	12.37	14.69	402,075	77,095.1

3.2 Construction of neural networks prediction model

This paper analysed an improved method based on artificial neural networks in the construction of neural networks prediction models, and studied the improvement methods of artificial neural networks. Among them, the error BP adopts the minimum quadratic function formula, converts the input and output of the index data into nonlinear optimisation, and uses the fastest Gradient descent to make the weight value conform to the negative gradient development direction of the error function. BP neural networks have broad application prospects in many fields due to their self-organising and self-learning characteristics, which can quickly process a large amount of data. However, BP neural networks also has some shortcomings.

Referring to relevant materials, it is concluded that the basic operation process of BP neural networks is information forward transmission and error reverse transmission (Xu et al., 2020). The forward propagation of information takes the processed data as an input layer, enters the hidden layer, and then outputs it. During the data transmission process, the weights and thresholds are fixed, and these neurons are affected vertically by downstream effects, while horizontally they are independent of each other; when the calculation result is not ideal, the error signal would be returned from the output layer to the input layer, and then the weights and thresholds between each neuron in the correction network would be adjusted sequentially until the ideal minimum error is obtained.

It is assumed that n and m are the input nodes and hidden nodes of the BP neural networks, respectively.

Among them, S_{i1}, S_{i2}, and S_{in} are indicator layers; r_{i1}, r_{i2}, and r_{in} are the input layers after standardisation of the indicator layer; ω_{jk} is the weight value from the *j*th node in the input layer to the *k*th node in the hidden layer; y_{ik} is the output of the hidden layer; ω_k is the weight value from the hidden layer to the output layer; o_i is the output value.

The formula for the hidden layer in the model is as follows:

$$y_{ik} = f\left(\sum_{j=1}^{n} W_{jk} r_{ij} - \theta_k\right) \tag{1}$$

Among them, θ_k represents the deviation value of hidden layer node k.

The output layer formula is as follows:

$$o_i' = g\left(\sum_{k=1}^{m} w_k r_{ik} - \theta\right) \tag{2}$$

Among them, θ represents the deviation of one output node in the output layer.

It usually has a bipolar S-type function (Liu et al., 2021).

$$f(x) = \frac{2}{1+e^{-ax}} - 1 \tag{3}$$

The total error function e of the true value o_i' relative to the expected value o_i is as follows:

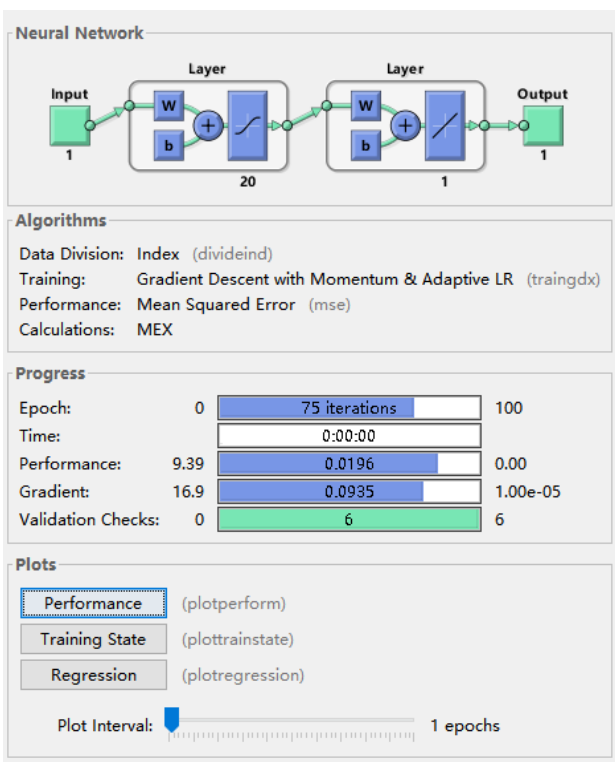
$$e = \sum_{i=1}^{h} \left(o_i' - o_i \right)^2 / 2 \tag{4}$$

3.3 Model training and optimisation

Based on the previous research on the construction of BP neural networks prediction models, this paper would use mathematical software to train and optimise the BP neural networks model.

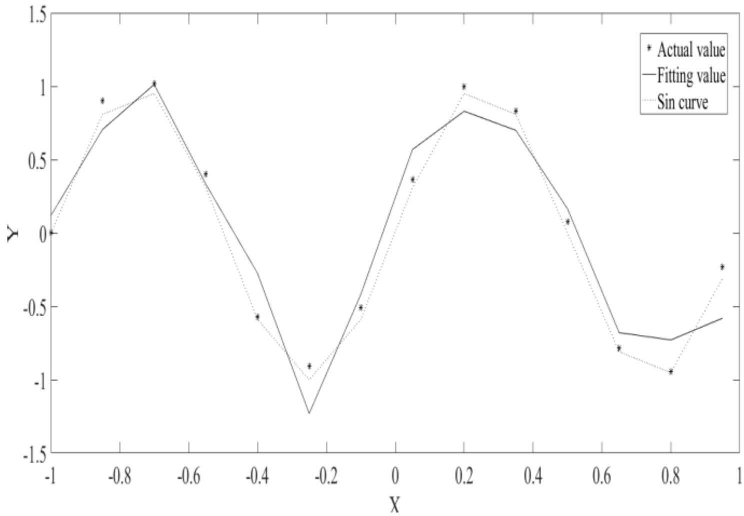
The direction of model training and optimisation this time is the gradient descent with momentum and adaptive LR (learning-rate). This method uses the first order guidance information and the second order guidance information. The training speed is much faster than the gradient method and the error function is the mean square error, which ingeniously avoids Hession matrix. Its disadvantage is that as the number of variables increases, the memory used also increases rapidly. Therefore, it consumes more memory and is not available when there are too many variables. It mainly studies the Mean squared error of the neural networks model. A total of 75 iterations have been conducted in the current 100 tests. The performance index performance value is 0.0196. 0.0935 is the current gradient value displayed in the progress bar, and the set gradient value is displayed on the right. If the current gradient value reaches the set value, the training would be stopped and the verification check would be 6. The specific summary is shown in Figure 2.

Figure 2 Setting of training parameters for BP neural networks (see online version for colours)



From Figure 2, it could be seen that there were three buttons under Plots, which were used to plot the performance map, training status, and regression analysis of the current neural networks. The training analysis of the neural networks is shown in Figure 3, as shown in Figures 4–6.

Figure 3 Training analysis of neural networks



The x-axis in Figure 3 represents the x-values within the range of [–1,1], while the y-axis represents the y-values within the range of [–1.5,1.5]. The legends are actual values, fitted values, and sin curves. It could be seen that there were 6 actual values on the sin curve in the figure. When the x value was within the range of [–0.8, –0.6], the actual value, fitting value, and sin curve values on the y-axis had the least difference. The maximum and minimum values of the fitted value curve corresponding to the y value within the range of x value [–1,1] were: When x was within the range of [–0.8, –0.6], the y value reached its maximum value; when x was within the range of [–0.4, –0.2], the minimum value of y appeared.

This paper uses the Min-Max normalisation method to standardise the data, scaling the input and output variables to the [0,1] interval to eliminate dimensional differences. Parameter tuning is achieved by combining grid search with cross-validation to optimise the learning rate, momentum term, and number of iterations to minimise the mean square error and improve the model convergence efficiency.

The x-axis in the figure represents the training times, and the y-axis represents the mean squared error. The legends are the training curve, validation curve, and optimal curve. It could be seen from Figure 4 that the best mean squared error was about 10^{-1}, and the best training times were about 69. From the trajectory of the validation curve and training curve in the graph, it could be seen that the training curve was lower than the mean square error of the optimal curve at the 69th training iteration. The mean squared error time of the training curve began to exceed the validation curve from the 6th time.

In Figure 5, the x-axis of group A, B, and C is the number of iterations, and the y-axis is the slope, inspection failure, and learning rate, respectively. The legends were training 1, 2, and 3. In Figure 5(A), the training state of the slope at the 75th training session was 0.093525; in Figure 5(B), the training state that failed validation at the 75th training session was 6; in Figure 5(C), the training state of learning rate at the 75th training was 0.25888.

Figure 4 Performance graph of neural networks

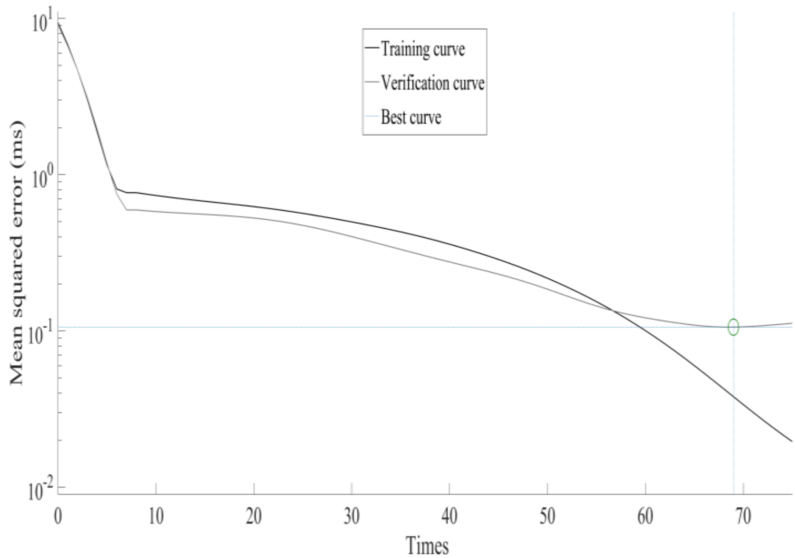
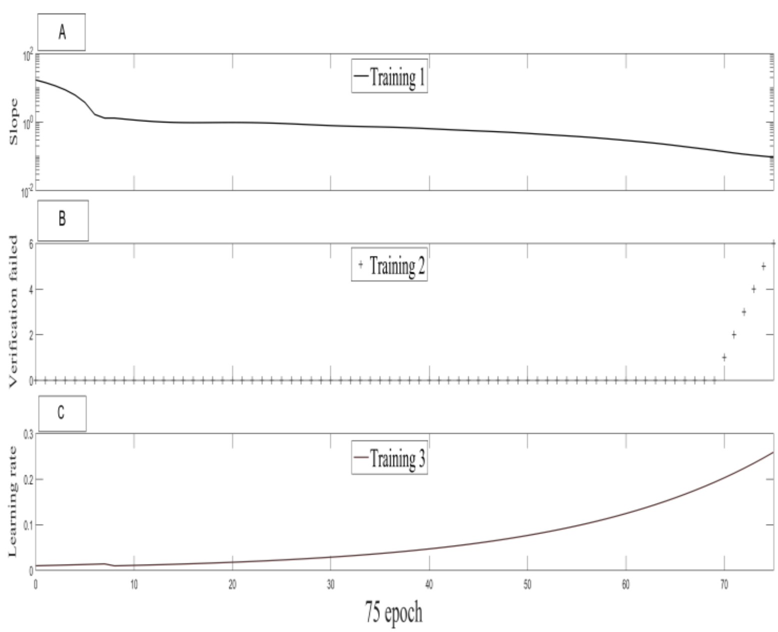
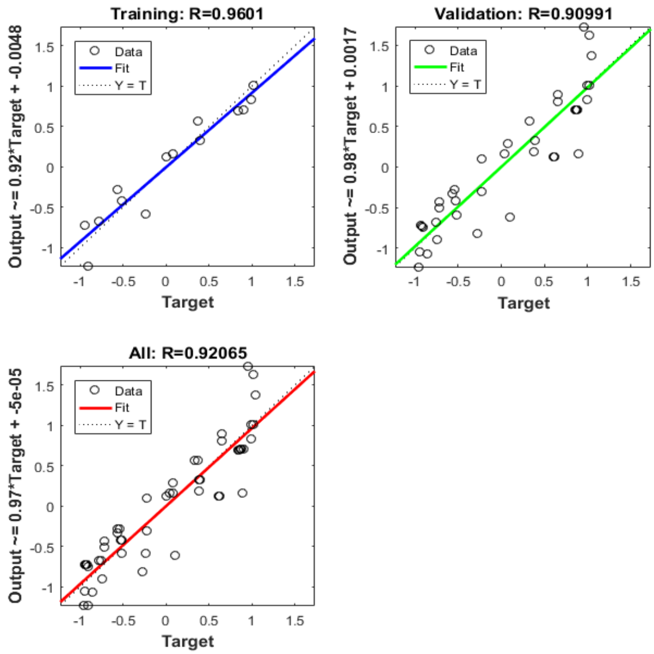


Figure 5 Training state of neural networks



Among them, in Figure 6, the output of the upper left image was 0.92*target value+0.0048, and the output of the upper right image was 0.98*target value+0.0017. The output in the left image was 0.97*target value+-5e-05.

Figure 6 Regression analysis of neural networks (see online version for colours)



The x-axis of the three group graphs in Figure 6 is the target value, and the y-axis is the output. The legends are data, fitting, and $Y = T$ curve. After testing, it was found that the R value of the BP neural networks during training here was 0.9601, and the R value during validation was 0.90991. According to the results obtained, the smaller the mean squared error was, the closer the R value was to 1, and the better the training effect was.

4 Evaluation of the relationship between CE, energy, and sustainable growth

4.1 Evaluation of interaction relationship

Based on the above research, this paper believes that the relationship between CE, energy and sustainable growth belongs to the category of relations between energy, environment and economy, but the interaction between energy, environment and economy is more complex. Energy is a factor of production that is the main driving force for economic growth, and the emissions generated during energy consumption can have an impact on environmental factors. At the same time, the consumed primary energy itself is part of the environmental and natural resources, and changes in environmental factors and the use of energy would have an impact on the long-term development of the economy. Therefore, there is a close interaction among the three, which determines the close connection between energy, CE, and sustainable growth. When the total or growth rate of fossil energy consumption is not proportional to the total or growth rate of the economy, it would shift from a role in promoting economic growth to a bottleneck restricting economic growth, thereby constraining sustainable economic development.

4.2 Evaluation of factors affecting CE

From the above data, it is not difficult to find that CE are the primary factor causing climate change today, and have attracted attention due to their cross-border nature. Against the backdrop of increasing CE year by year, how to effectively reduce their CE is an important issue that urgently needs to be solved. On this basis, this paper took energy consumption, economic growth, energy efficiency, and energy composition as the research objects, used correlation analysis method to quantify the correlation between various factors and CE, and ranked the correlation degree of each factor to determine the intensity of each factor's impact on CE.

Mineral energy is essentially a carbon based energy source, which generates a large amount of CO_2 during utilisation, leading to an increase in CE. The CE involved are relatively broad, and various economic activities can lead to an increase in CE in the process of promoting economic growth.

5 Experimental evaluation of trend prediction using neural networks

This paper took the average annual car sales in China as an example to analyse the relationship between the fuel used and the gas discharged by cars under the economic growth driven by car sales. Table 5 shows the total car sales and growth rate in China from 2019 to 2023:

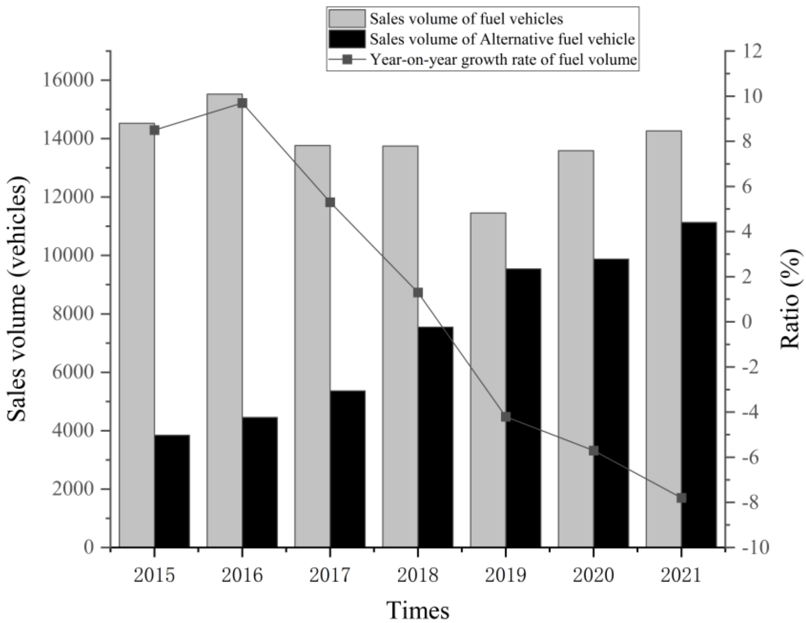
Table 5 Total automobile sales and growth rate in china from 2019 to 2023

Time	*Total sales volume* (*10000 units*)	*Growth rate* (%)
2019	2557	/
2020	2503	–2.1
2021	2605	4
2022	2666	2.3
2023	2845	6.7

Table 5 shows that the overall sales of automobiles in China from 2019 to 2023 show an upward trend. Compared to 2019, the year-on-year growth rate in 2020 showed negative growth. By 2021, the year-on-year growth rate reached 4% compared to the previous year. In 2022, the year-on-year growth rate reached 2.3% compared to the previous year. Here, a forecast for 2023 was also made based on the total sales in previous years. It could be seen that in 2023, there was an actual increase of 179 compared to the previous year, with a year-on-year increase of 6.7%. Based on the above data, it could be seen that China's car ownership was still continuously increasing. In view of how to solve the problems of energy consumption and CE, this paper analysed fuel vehicles and alternative fuel vehicle.

An economically developed city was selected to forecast its sales volume and fuel consumption in the next year based on the sales volume of fuel vehicles and alternative fuel vehicle in previous years, as shown in Figure 7.

Figure 7 The year-on-year growth rate of car sales and fuel in the region from 2015 to 2021



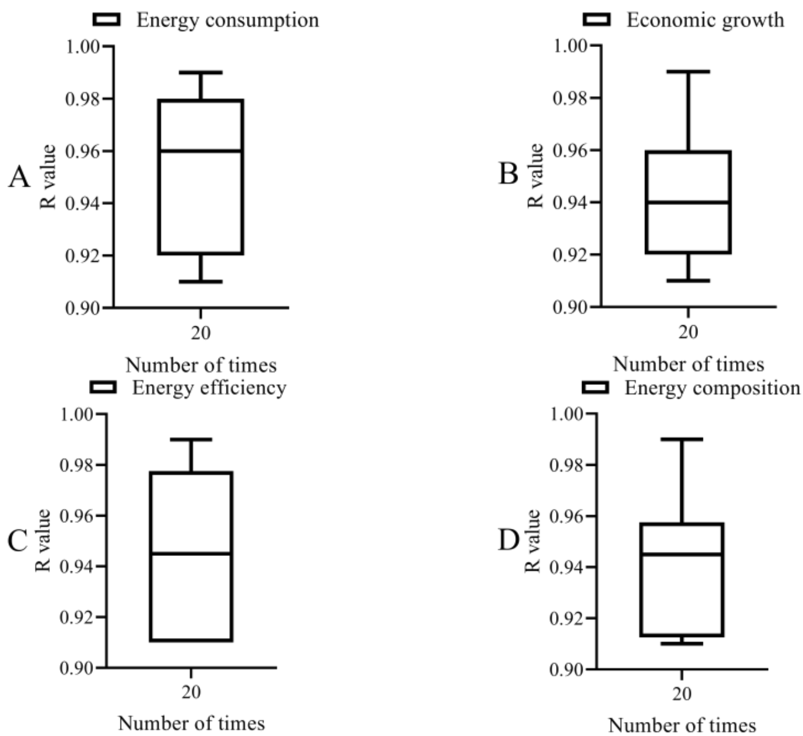
The x-axis in Figure 7 represents time. The left y-axis represents sales volume, and the right y-axis represents ratio. The figures are the sales volume of fuel vehicles, the sales volume of alternative fuel vehicle and the year-on-year growth rate of fuel volume. It could be seen from the figure that the annual sales volume of fuel vehicles was more than that of alternative fuel vehicle. However, with the change of time, the sales of fuel vehicles in the area began to decrease from 2016 until the sales rebounded in 2019; the annual sales volume of alternative fuel vehicle in 2015 was much lower than that of fuel vehicles. However, with the continuous progress of new energy vehicle technology, people were also gradually choosing such vehicles, and their total sales were continuously increasing during the period of 2015 to 2021. For automotive fuels closely related to fuel vehicles, it could be seen from the fuel year-on-year growth rate line in the figure that the year-on-year growth of fuel was continuously decreasing since 2016, and even showing negative growth in 2019. Therefore, it could be seen from the changes of the above three factors that the ownership of alternative fuel vehicle was growing as the number of fuel vehicles was decreasing. At the same time, the fuel required for fuel was gradually decreasing, which could to some extent control the total amount of CE and achieve the goal of carbon neutrality.

Based on the training results of the BP neural networks model mentioned earlier, the factors affecting CE were discussed and their correlation coefficient R values were analysed, as shown in Figure 8.

The x-axis in Figure 8(A)–(D) represents the degree, while the y-axis represents the R-value. The legends are energy consumption, economic growth, energy efficiency, and energy composition. Figure 7 shows the correlation coefficient analysis of factors affecting CE. From Figure 8, it could be seen that under the prediction of the neural networks model, the R-value range of the above four influencing factors was between

[0.91–0.99]. The difference lied in four instances of energy consumption with an R-value of 0.99, one instance of economic growth, three instances of energy efficiency, and two instances of energy composition. Therefore, it could be seen that there was a higher correlation between energy consumption and CE.

Figure 8 Correlation coefficient analysis of factors affecting CE: (A) R-value of energy consumption; (B) R-value of economic growth; (C) R-value of energy efficiency and (D) R value of energy composition



In summary, there is currently a lack of coordination in the development of many regional economies. Different regions should combine their own development characteristics, leverage their regional advantages, and transform their disadvantages, so as to rely on energy consumption to achieve economic growth. They should enhance renewable energy, and develop regions into energy market liberalisation, thus striving to achieve carbon neutrality as soon as possible.

It is recommended to implement a tiered carbon tax (such as levying tiered taxes on high-carbon emission industries based on emissions), and simultaneously implement subsidies for renewable energy research and development and financial support for infrastructure construction; establish an international carbon trading market mechanism, incentivise the transfer of emission reduction technologies through quota trading, and set up an energy transition fund for developing countries to strengthen international cooperation on low-carbon technologies.

6 Conclusions

Energy consumption and environmental issues are hot topics of general concern to the international community. At present, the global warming problem caused by excessive carbon dioxide emissions has become one of the key factors threatening human survival and development. The international community generally believes that reducing greenhouse gas emissions, especially carbon dioxide emissions, is the best way to solve this problem. This paper used neural networks to analyse and predict the relationship and trends between CE, energy, and sustainable growth. The data was organised in five regions: North America, South America, Europe, Asia Pacific, and Africa. The relevant data on CE, energy efficiency consumption, and energy structure were analysed. The neural networks prediction model was studied and optimised using software for training. The results section provided examples for combined research, and concluded that energy consumption and economic growth belonged to a causal relationship, while there was a correlation between economic development and CE.

This study has the following limitations: the data timeliness is limited to 2021, and does not cover recent policies (such as the impact of the Russia-Ukraine conflict on the energy structure); the model is not interpretable enough, and the black box characteristics of the BP neural network affect the transparency of the mechanism; the regional heterogeneity analysis is relatively rough, and does not deeply subdivide energy types (such as differences between coal and oil); the dynamic regulatory effects of exogenous variables such as policy intervention and technological innovation on carbon emissions are not included. This paper will introduce population growth, international trade and technology policy variables to construct a multivariate coupling model; strengthen cross-regional heterogeneity analysis and dynamic feedback mechanism to improve prediction accuracy and policy adaptability.

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Conflicts of interest

The authors declare no conflict of interest.

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