Global Green GDP Forecasting Model Based on BP Neural Network

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Abstract: Multilateral developments would present a challenge to the global harmonization of green GDP as the fundamental criterion of economic health. Green GDP, on the other hand, considered environmental costs and sustainability and contributed to effective global climate crisis. mitigation in contrast to GDP, which was currently used to gauge national economic performance.We built a model of expected global climate mitigation based on BP neural networks. Secondly, to create climate evaluation indicators based on CO2 emissions and temperature variations, seven variables from four typical nations were integrated with GDP. The GGDP data for the USA was added to the model for validation utilizing the test set to examine the generalization capability of the BP neural network. It was discovered that the changing trend was essentially consistent, illustrating that the model had stability.

Keywords: Combination weight, Leslie model, Neural network, Climate change

1. INTRODUCTION

The gross domestic product (GDP) was one statistic used to gauge the rate and magnitude of economic expansion, but it overlooked other considerations including resource consumption and environmental harm[1][10]. For human society to evolve sustainably, environmental and resource cost accounting had to be integrated into national economic accounting. The foundation for attaining harmonious sustainable development was the GGDP accounting system, which organically fused economic progress with the environment[3]. The need for environmental services that offered resources and eliminated waste had been growing quickly as economic development and consumption had improved. Resources and environmental services had long been used as public resources without being paid for due to the absence of a matching market mechanism, making it impossible to distribute them optimally through market mechanisms.

By tracking and evaluating global impact setting data, we developed a stable model that substituted GDP as the standard for projecting the anticipated worldwide influence on climate. Green economy and sustainable development is a new perspective to study urban economy in recent years. Chiu et al. [4] evaluated the economic benefits of green ports from the dimensions of resource utilization, waste treatment, environmental greening and social input. Yin et al. [5]

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took China as an example to build a transportation planning model, promote energy conservation and emission reduction, and promote the sustainable economic development of coastal cities and hinterland. Liao Shaoxu et al. [6] evaluated low-carbon development and found that urban green development was at a higher level. Chen and Lam[7]proposed a method to measure the sustainable development of urban systems by using the two-stage data network method. Liu et al.[8] adopted the THPD model to evaluate urban sustainability and expanded the sustainability theory with port city as the research object to provide directions for sustainable urban development.

2. MODEL ESTABLISHMENT AND SOLUTION

we examined the shifting relationships between climate effect variables and climate cuts, built a nonlinear mapping relationship between them, solved the problem using a machine learning model, and then examined the model's stability utilizing the U.S as an example.

2.1 Predicted impact model of climate mitigation based on BP neural network

2.1.1 BP neural network model and training effect

We constructed a functional link with climate parameters and utilized temperature and CO2 as evaluation markers for climate change.

$$(Y_1, Y_2) = f(X_1, X_2, \ldots, X_8) \tag{1}$$

Where X1~X7 are the corresponding direct and indirect climate consumption costs, X8 was the GDP data.

The presence of cointegration between the variables and the overall person correlation coefficient was then tested utilizing Pearson correlation analysis[2].

$$\rho_{XY} = \frac{Cov(X,Y)}{\sigma_X \sigma_Y} = \frac{\sum_{i=1}^{n} \frac{(X_i - E(X))}{\sigma_X} \frac{(Y_i - E(Y))}{\sigma_Y}}{n} \tag{2}$$

σx is the standard deviation of X

$$\sigma_X = \sqrt{\frac{\sum_{i=1}^{n}(X_i - E(X))^2}{n}}, \sigma_Y = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - E(Y))^2}{n}} \tag{3}$$

$$|\rho_{XY}| \le 1, \text{ when } Y = aX + b, \ \rho_{XY} = \begin{cases} 1 & a > 0 \\ -1 & a < 0 \end{cases}$$

On this basis, the correlation was shown in the form of thermal map as Figure 1 drawn.

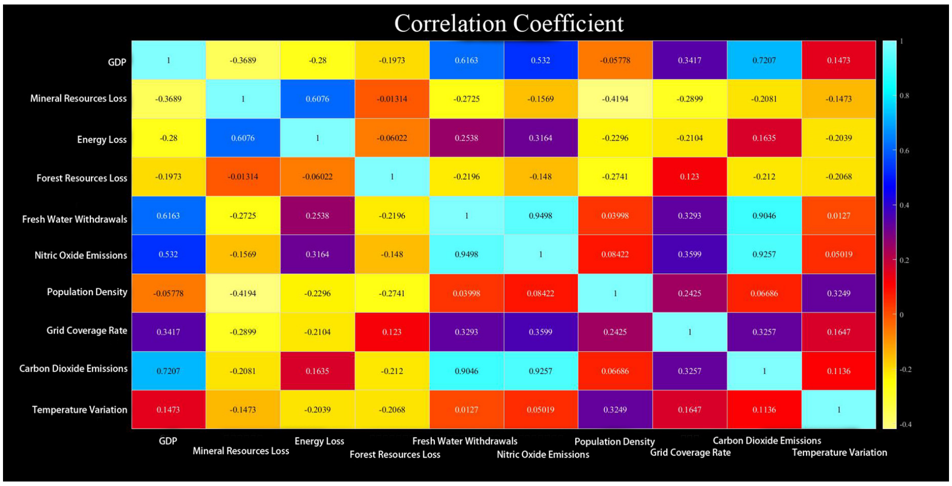

Figure 1 Heat map of the correlation between climate consumption costs and climate change

The heat map plot demonstrated that there was no statistically significant link between the variables, and all of the input variables were used in the machine learning process.

For the training of the BP neural network model, we utilized 8 climate-influencing elements as input variables and 2 climate change indicators as output variables.

A chain partial differential was utilized for the core content weights and threshold adjustment amount in a multi-parameter BP neural network[4].

$$\Delta w_{jk} = -\eta \frac{\partial E}{\partial w_{jk}} = -\eta \times (Y - O_3) \times O_2 \quad \Delta B_{jk} = \frac{\partial E}{\partial w_{jk}} = -\eta \times (Y - O_3) \times ones \tag{4}$$

Amount of adjustment of weights and thresholds between layers (5) and (6).

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial B_{ij}} = -\eta \times w_{jk} \times (Y - O_3) \times O_2 \times (1 - O_2) \times X \tag{5}$$

$$\Delta B_{ij} = -\eta \frac{\partial E}{\partial B_{ij}} = -\eta \times w_{jk} \times (Y - O_3) \times O_2 \times (1 - O_2) \times ones \tag{6}$$

Adjusted weights and thresholds:

$$\begin{aligned} w_{jk}(t+1) &= -\eta \frac{\partial E}{\partial w_{jk}} + w_{jk}(t) = \Delta w_{jk} + w_{jk}(t) \\ B_{jk}(t+1) &= -\eta \frac{\partial E}{\partial B_{jk}} + w_{jk}(t) = \Delta B_{jk} + B_{jk}(t) \end{aligned} \tag{7}$$

$$w_{ij}(t+1) = -\eta \frac{\partial E}{\partial w_{ij}} + w_{ij}(t) = \Delta w_{ij} + w_{ij}(t)$$

$$B_{ij}(t+1) = -\eta \frac{\partial E}{\partial B_{ij}} + B_{ij}(t) = \Delta B_{ij} + B_{ij}(t)$$

The data set was randomized while the model was being trained. The cut training set and validation set percentages were 80% and 20%, respectively. After performing normalization and denormalization, the model's final training result was displayed in Figure 2.

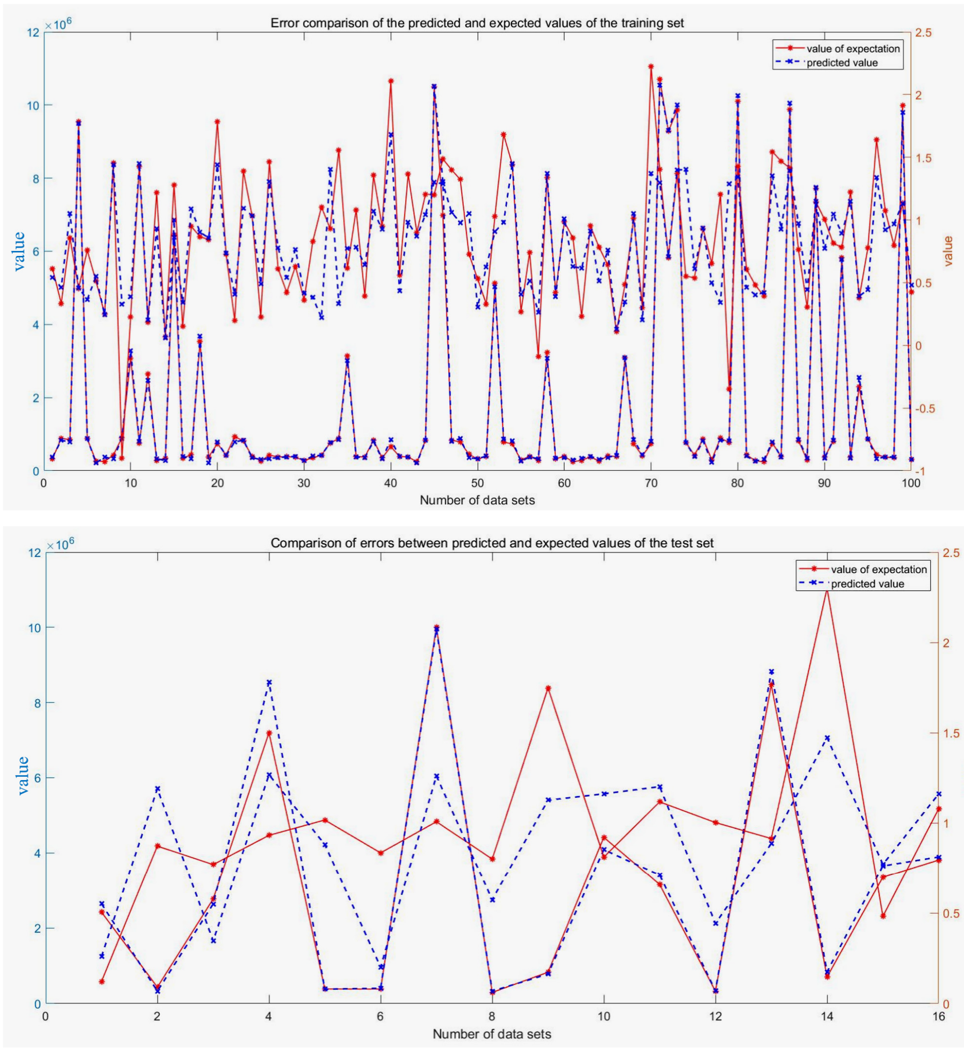

Figure 2 Fit of the predicted and actual values of the training set based on BP neural network model

2.1.2 Evaluation of generalization ability of BP neural network model

We analyzed the generalization ability of the BP neural network model by a test set[5]. The actual vectors of 16 samples of temperature and CO2 in the test set. $y=[y_1,y_2,\dots,y_{16}]$ and $y^{'}=[y_1^{'},y_2^{'},\dots,y_{16}^{'}]$ denoted that the predicted values of temperature and CO2 obtained by the established BP neural network for 16 samples were vectors: $\hat{y}=[\hat{y}_1,\hat{y}_2,\dots,\hat{y}_{16}]$ and $\hat{y}^{'}=[\hat{y}_1^{'},\hat{y}_2^{'},\dots,\hat{y}_{16}^{'}]$. The equation was shown below.

R2 is Fitting coefficient

$$R^2=1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\overline{y_i})^2} \tag{8}$$

RMSE was root mean square error:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2} \tag{9}$$

MAE was the average absolute error:

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left|y_i-\hat{y}_i\right| \tag{10}$$

MAPE was the mean absolute percentage error:

$$MAPE=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \tag{11}$$

2.2 Validation of the model by green GDP data

We examined the impact of GGDP statistics on the magnitude of temperature and CO2 variations across various nations. Using GDP and seven more influencing parameters as input variables, more temperature than CO2 as output variables, we trained the model using a BP neural network with four different countries, each with unique characteristics[6].

To assess the actual trends of temperature and CO2 changes, trends of temperature and CO2 changes based on the GGDPs, which were first estimated independently for the four nations and validated using weights obtained using the combined assignment technique, as shown in Figure 3.

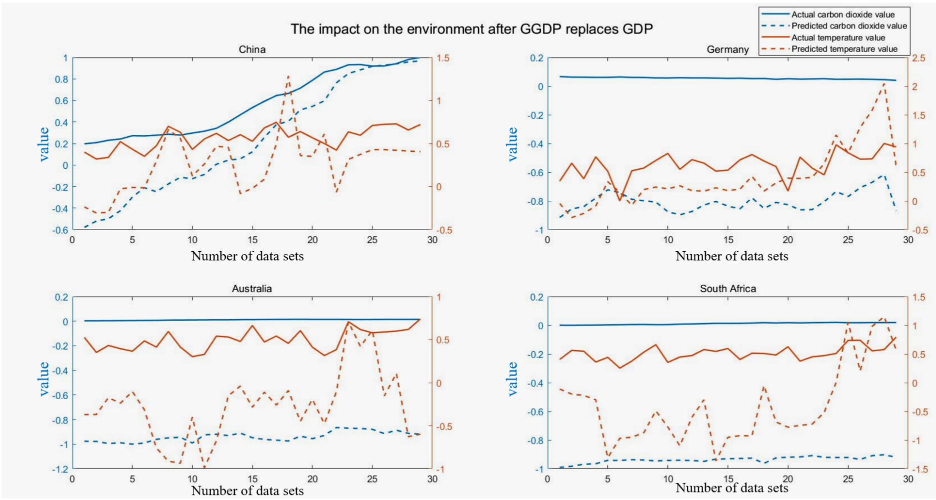

Figure 3 Analysis of climate mitigation trends in 4 representative countries

Considering the findings from four representative nations, it was determined that GGDP had a worldwide impact on the climate and that there was no overall change when GDP was replaced with GGDP.

2.3 Validation of the model with USA data

We compared data from the U.S to data from the other four continents to see whether there was any correlation between them[7]. For validation, we generated the GGDP data and climatic parameters for the United States, added them to the trained model, and checked to see if the temperature and CO2 trends were consistent across the five continents, as illustrated in Figure 4.

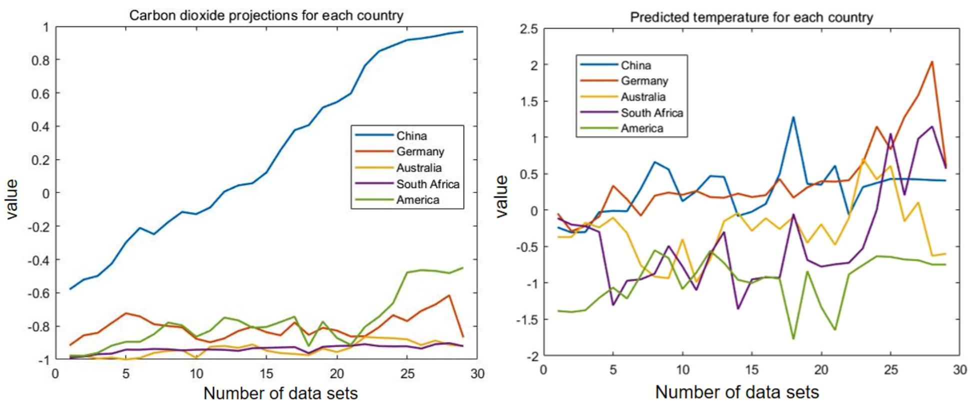

Figure 4 The GGDP data validation set for the USA compared to the other 4 countries

2.4 Model stability test

Taking into account that the model's direct and indirect corrections' parameters came from objective assignments. To account for the influencing climate aspects, we merged numerous subjective criteria, such as geographic circumstances and political history[8][9].

Four sets of comparison experiments were designed with correction coefficients of 0.3, 0.4, 0.5 and 0.8 for direct climate factors and 0.7, 0.6, 0.5 and 0.2 for indirect climate factors, respectively to observe whether the model remained stable with different weight corrections. This is shown in Figure 5.

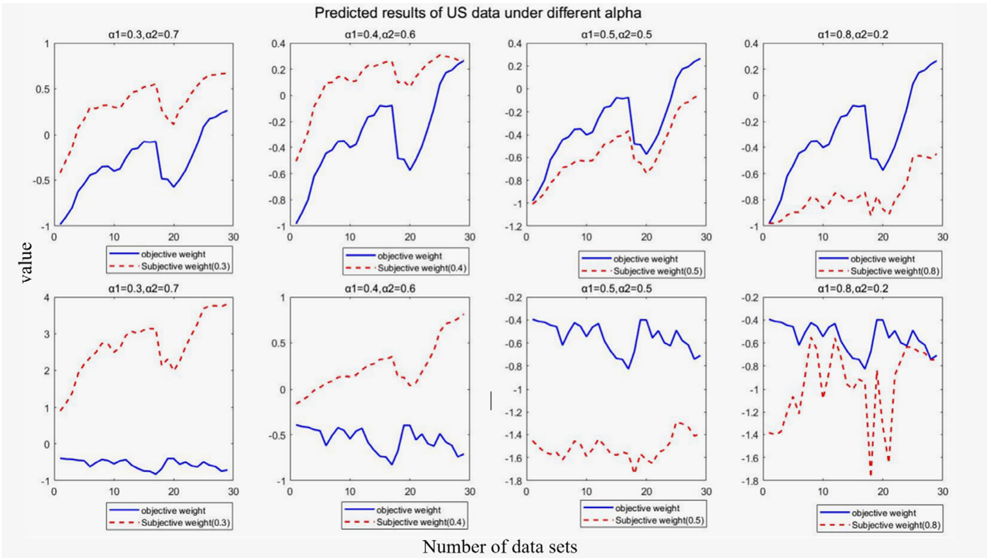

Figure 5 The change trend of temperature and CO2 compared with the original control group under different weight correction coefficients

Using various adjustment settings, the pattern of change stayed consistent, the CO2 emissions remained constant, and the temperature trended upward. The results of calculating each corrective model's generalization capacity were displayed in Table 1.

Table 1 Test of model generalization ability with different weight correction coefficients

	α_1=0.3	α_2=0.4	α_3=0.5	α_4=0.8
R^2	0.70956	0.72782	0.74949	0.72216
RMSE	0.21019	0.24715	0.21926	0.20747
MAE	0.16103	0.1886	0.17156	0.16297

3. CONCLUSION

Through the development of the GGDP model, the actual economic health of the nation was assessed. A thorough investigation was conducted into the GGDP model created by varying the weights and including impact indicator characteristics. We examined information from 5 countries that represented global data based on the impact of climate change, taking into account both direct and indirect impact factors brought on by climate, and we used a combination of weighting methods to more precisely analyze the weight size of each indicator.

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