Developing a Green GGDP Calculation Model to Predict the Impact of Global Climate Mitigation

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***Abstract*—In recent years, with global greenhouse gas emissions increasing year on year and the destruction of the natural environment and ecosystems, a climate crisis has arrived upon us, and a global campaign to protect the betterment of humanity seems urgent. As a consequence, a green GDP conversion action was opened up. We simulated the replacement of GDP by green GDP as a key indicator of a country's economic health, integrated global considerations of the expected impacts of climate mitigation. We first choose the GGDP as the basic calculation model. Further, we propose a direct loss cost (M1) and an indirect loss cost (M2) for climate impacts, making improvements to the GGDP calculation model. Further, because M1 and M2 contribute differently to climate impacts, we attribute different weights to each. Finally, we use entropy weighting method for the solution of the weights, the weights for M1 and M2 were found to be 0.5464 and 0.4536 respectively. We first choose CO2 emissions and annual average temperature change as indicators to evaluate the global impact of climate mitigation. Further, we use a improved BP neural network for the training of the model and optimize the threshold and connection weights of the BP neural network based on a genetic algorithm. Finally, temperature changes and CO2 emissions are simulated and forecast for four countries.**

***Keywords*—BP neural network, genetic algorithm, green GDP, climate crisis**

I. Introduction

In recent years, the increasing GDP of countries has been followed by a yearly increase in global greenhouse gas emissions, a growing climate crisis, the destruction of the natural environment and ecosystems[1], as well as the end of our beautiful home.Figure 1 shows Global emissions of various greenhouse gases, we can see the global emissions of several greenhouse gases from 1990 to 2021[2].

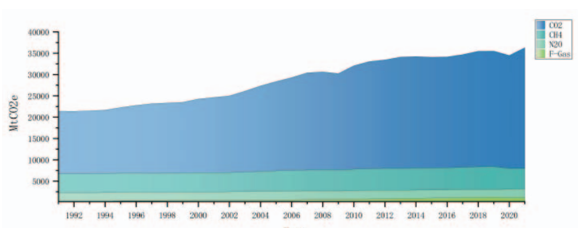

Figure 1 Global emissions of various greenhouse gases (1990-2021)

In the face of today's severe climate crisis, we have to consider environmental and sustainability perspectives and factors.Changing the way countries assess and compare their economies will not only help governments to change their behaviour[3], but will also contribute to the enactment of policies and projects for the health of the planet, and Green GDP (GGDP) is a valuable way of assessing this.

However, we are not sure whether GGDP can be a better measurement than the current traditional GDP.Therefore, when GGDP is the main indicator of a country's economic health, the resulting changes and the impact of these changes on climate mitigation and the environment are of concern to countries[4]. This is what our model needs to go on to address.

II. Green GDP mathematical model construction

We understand how GGDP is calculated and the formula, GGDP = GDP - EnDC - EcDC, but with such a broad formula alone, it cannot be shown to have a significant impact on climate mitigation.By taking into account the different regions of the world, the direct loss costs include the loss of minerals, energy, forests and fresh water; the indirect loss costs include carbon monoxide emissions, carbon dioxide emissions, temperature changes due to carbon dioxide emissions, changes in population density, and changes in the rate of electricity, resulting in the following equation[4].

$$GGDP_1 = GDP - M - N$$

Since the contribution of direct and indirect depletion costs to climate-induced GDP losses is inconsistent, this led to the introduction of an entropy weighting approach to improve the model.

$$GGDP_2 = a_1 M - a_2$$

In the above, we introduced 9 indicators related to them, with China, Germany, South Africa, Australia representing their respective continents, to characterise the global impact of climate mitigation, and we collected reliable data on authoritative websites to determine the weights.

A. Entropy Method Calculation

We first normalise the data for each indicator to obtain a normalised matrix of direct and indirect losses:

$$Z_{ij}, (\mathrm{i} = 1,2;\ \mathrm{j} = 1,2, \ldots, 9)$$

From there, the weight of each of these indicators is calculated:

$$P_{ij} = \frac{Z_{ij}}{\sum_{i=1}^{2} Z_{ij}}, (\mathrm{i} = 1,2;\ \mathrm{j} = 1,2, \ldots, 9)$$

In the above, we introduced 9 indicators related to them, with China, Germany. Further, we calculate the information entropy, i.e. the uncertainty, for each indicator.

$$e_j = -\frac{1}{ln9}\sum_{j=1}^{9} P_{ij}\ln\left(P_{ij}\right), (\mathrm{i} = 1,2;\ \mathrm{j} = 1,2,\ldots,9)$$

The calculation of information utility values is then carried out:

$$d_j = 1 - e_j, (\mathrm{j} = 1,2,\ldots,9)$$

The final normalised bit is used to calculate the weights:

$$w_j = \frac{d_j}{\sum_{j=1}^{9} d_j}, (\mathrm{j} = 1,2,\ldots,9)$$

Direct wastage cost weights:

$$\alpha_1 = \omega_1 + \omega_2 + \omega_3 + \omega_4$$

Indirect wastage cost weights:

$$\alpha_2 = \omega_5 + \omega_6 + \omega_7 + \omega_8 + \omega_9$$

B. Algorithm Flow and Results

We solved it via Matlab and the algorithm flow chart is shown in Figure 2.

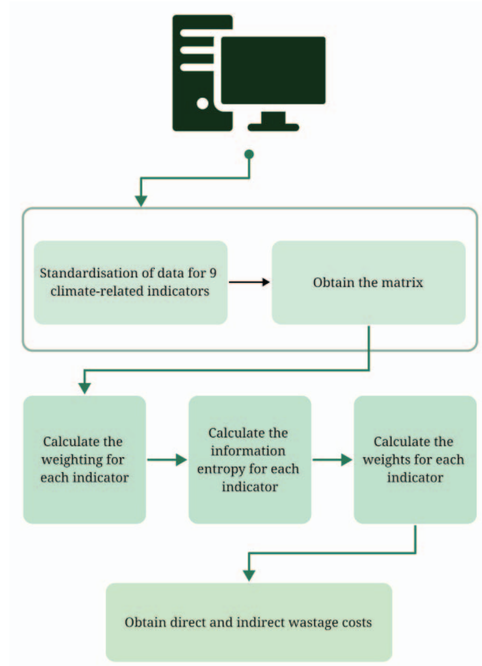

Figure 2 Algorithm flow chart

Finally solution of the weights for different representative countries[5], ω_1 represents depletion of mineral resources, ω_2 represents the amount of energy lost, ω_3 represents net depletion of forest resources, ω_4 represents annual freshwater abstraction, ω_5 represents carbon monoxide emissions, ω_6 represents CO_2 emissions, ω_7 represents the temperature change resulting from CO_2 emissions, ω_8 represents change in population density, ω_9 represents the change in the rate of energisation[6]. Table I shows weights of different representative countries.

TABLE I WEIGHTS OF DIFFERENT REPRESENTATIVE COUNTRIES

Representative countries	ω_1	ω_2	ω_3	ω_4	ω_5	ω_6	ω_7	ω_8	ω_9
CHN	0.005	0.338	0.181	0	0.053	0.19	0.064	0.153	0.021
DEU	0.007	0.297	0.307	0	0.046	0.046	0.118	0.165	0.014
ZAF	0.006	0.134	0.239	0	0.248	0.23	0.014	0.017	0.112
AUS	0.006	0.332	0.241	0	0.133	0.034	0.095	0.031	0.128

TABLE II DIRECT AND INDIRECT LOSS COST WEIGHTS FOR DIFFERENT COUNTRIES

Representative countries	CHN	DEU	ZAF	AUS
α_1	0.519	0.611	0.379	0.579
α_2	0.481	0.389	0.621	0.421

Table II shows direct and indirect loss cost weights for different countries. From the table II, we calculate the weights for the direct and indirect damage costs, and the results are α_1=0.5464, α_2 =0.4536.GGDP is calculated using the formula: GGDP=GDP-0.5464M1-0.4536M2.

III. AN EXPECTATION MODEL FOR GLOBAL CLIMATE MITIGATION BASED ON IMPROVED BP NEURAL NETWORKS

A. Evaluation and Training of Improved BP Neural Network Models

We chose CO_2 emissions and average annual temperature change as evaluation indicators to determine whether they change when GGDP is used instead of GDP[7].When conducting forecasting with a BP neural network model, it is necessary to conduct a correlation analysis to help us better determine the inputs to the BP neural network. We used a chi-square correlation analysis to obtain the following heat map of the correlation between the nine indicators and GDP[8],as shown in Figure 3.

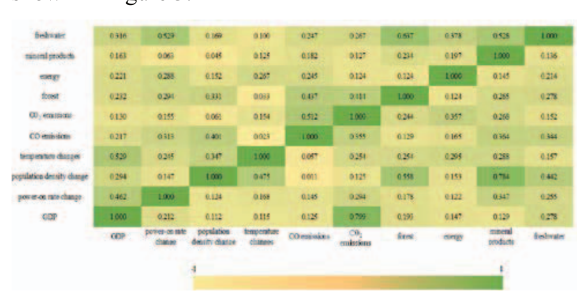

Figure 3 Relevance Heat Map

From the above figure, we can see that there is no strong correlation between the ten indicators, so there is no need to eliminate the input indicators. We can use the ten indicators as the input to the BP neural network, by the formula $n = 2m + 1$ [9](n is the number of hidden nodes, m is the number of inputs), then we get the number of hidden nodes is 21, the output is CO2 emissions and annual average temperature change. Figure 4 shows the structure of the neural network.

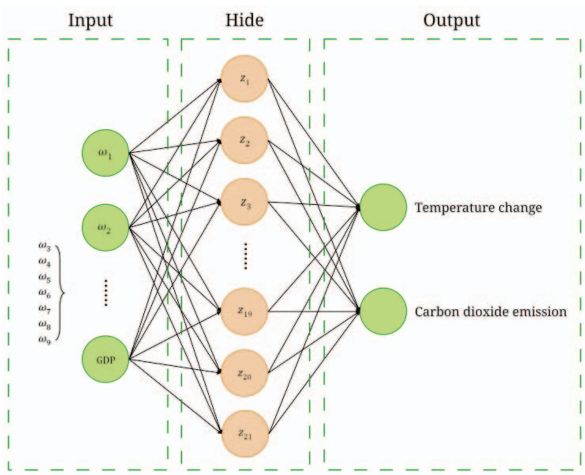

Figure 4 Neural network structure diagram

We disrupted the data and randomly selected 85% and 15% as the training and validation sets, respectively, to obtain the results shown in the Figure 5.

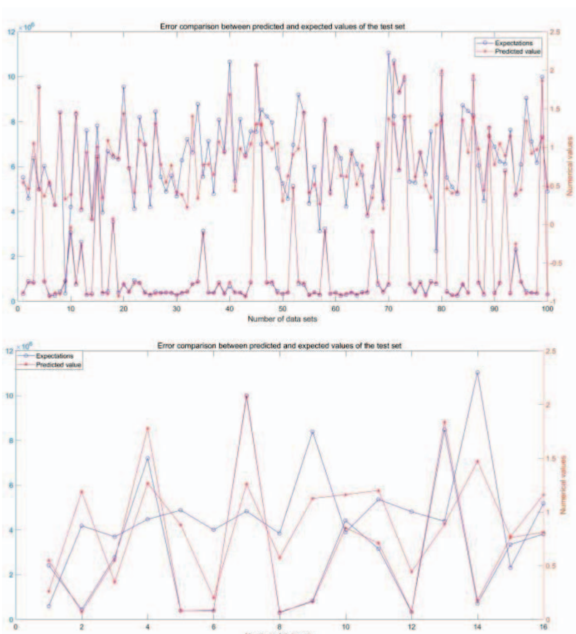

Figure 5 Neural network model training results

Finally, we objectively evaluated the model built by the improved BP neural network through three metrics. Table III shows the evaluation indicators and results

TABLE III EVALUATION INDICATORS AND RESULTS

Indicator	Implication	Result
R^2	Fit coefficient	0.8726
RMSE	Root mean square error	0.1354
MAPE	Absolute percentage error	9.742%

With the results of the three evaluation indicators as above, it can be found that the model fits well and the absolute percentage error, although 9.74%, does not affect the results of the long-term climate mitigation projections. This shows that the model training results are good.

B. Expected Global Impacts of Climate Mitigation

The GGDP for China, Germany, Australia and South Africa was calculated based on the green GDP calculation method and the weights obtained in question one[10], and then after training according to the training model method described above, the GGDP was substituted for GDP for predicted CO2 emissions and annual average temperature, and then the results were compared with the actual situation.

Figure 6 shows the diagram of the expected results of climate mitigation

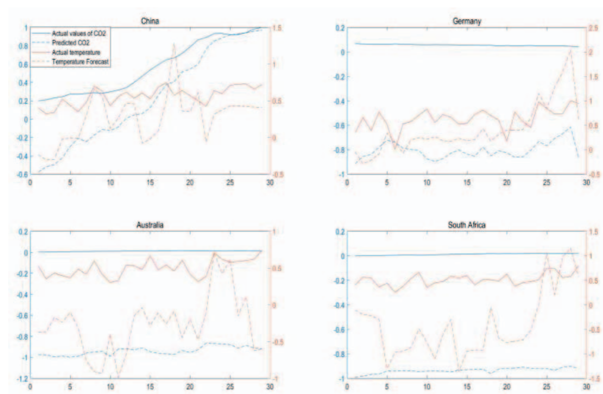

Figure 6 Diagram of the expected results of climate mitigation

When the above graph is analysed, the expected global impact of climate mitigation when using Green GDP instead of GDP[11], it is found that CO2 emissions and average annual temperature change for all four countries are lower than they actually are, with the exception of a few values, and the two curves rise more gently[12]. This leads to the conclusion that green GDP is beneficial for climate mitigation when used as a primary measure of a country's economic health instead of GDP[13].

IV. CONCLUSION

In recent years, with global greenhouse gas emissions increasing year on year and the destruction of the natural environment and ecosystems, a climate crisis has arrived upon us, and a global campaign to protect the betterment of humanity seems urgent.As a consequence, a green GDP conversion action was opened up.We simulated the replacement of GDP by green GDP as a key indicator of a country's economic health, integrated global considerations of the expected impacts of climate mitigation. we first choose the GGDP as the basic calculation model.Further, we propose a direct loss cost (M1) and an indirect loss cost (M2) for climate impacts, making improvements to the GGDP calculation model.Further, because M1 and M2 contribute differently to climate impacts, we attribute different weights to each.Finally, we use entropy weighting method for the solution of the weights, the weights for M1 and M2 were found to be 0.5464 and 0.4536 respectively.we first choose CO2 emissions and annual average temperature change as indicators to evaluate the global impact of climate mitigation.Further, we use a improved BP neural network for the training of the model and optimize the threshold and connection weights of the BP neural network based on a genetic algorithm.Finally, temperature changes and CO2 emissions are simulated and forecast for four countries.In this article, we can see that the adoption of Green GGDP instead of GPD as the main indicator of a country's economic development has been found to be beneficial in mitigating the climate crisis through the selected CO2 emissions and temperature changes.

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