Study on the Relationship between Global Hurricane and Global Warming

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Abstract. In order to measure the intensity of global hurricanes, this paper selects the frequency of hurricanes, the average grade and the mean wind speed as the indexes of intensity. Firstly, the annual hurricanes frequencies in the Atlantic Ocean, the Western Pacific, the East Pacific, the North Indian Ocean and the South Indian Ocean and the global average hurricanes scale and average wind speed, train the existing data through wavelet neural network and predict the occurrence frequency of hurricanes in the next 20 years. According to the scatter plot drawn from the known data, it is found that the global hurricane frequency, the average grade and the average speed of wind, which showing periodic changes, but generally increase. As a result, the intensity of global hurricanes has generally been enhanced in the current phase of observations.

1. Introduction

A research paper written by Peter Webster, a professor at George Institute of Technology in the United States, and a research paper published in the United States of Science said about 4 times and 5 levels of hurricanes occurred globally each year on average in the 1970s [1]. After the 1990s it reaches as many as 18 times a year, almost doubled. Kerry Emanuel, an atmospheric scientist at the Massachusetts Institute of Technology, also found that the potential destructive power of hurricanes in the North Atlantic more than doubled over the past 50 years, while the destructive power of the typhoon in the Northwest Pacific increased by about 75%. Some scientists believe that the reason why hurricanes were formed only in the tropical oceans is because high-temperature seawater is a source of hurricane energy [2]. So they infer that the production of hurricanes is related to global warming [3]. Nevertheless, the scientific community continues to question this. Storm forecasting experts believe that the Atlantic storm is part of the normal cyclical cycle. There is no direct indication that warming is linked to a global increase in hurricanes. To further identify which viewpoints are more scientific and rational, we will model the relationship between global warming and the formation of hurricanes.

Therefore, in this paper, we use the principles and methods of system dynamics to establish a global temperature system SD model from the characteristics of the global temperature, the model boundaries and elements causality of the system. Then to analyze the global temperature rise Multiple Feedback Mechanism and System Interaction Process [4]. A gray neural network model based on gray GM (1,1) prediction model and artificial neural network prediction model is used to predict the global atmospheric temperature [5]. This method uses the artificial neural network to grasp the unknown relationship between the predicted value and the actual value obtained by the gray GM (1,1), and then makes a new prediction.
2. Gray neural network topology

A gray neural network model based on gray GM (1,1) prediction model and artificial neural network prediction model is used to predict the global atmospheric temperature. This method uses the artificial neural network to grasp the unknown relationship between the predicted value and the actual value obtained by the gray GM (1,1), and then makes a new prediction. Gray problem refers to the prediction of the development and change of eigenvalues of uncertain gray system behavior. The sequence \( x_r^{(0)} (t = 0,1,2,...N-1) \) of the original sequence \( x_r^{(i)} \) of eigenvalues of gray system after exponentiation increases exponentially, so a continuous function or differential can be used equations for data fitting and prediction. For convenience of expression, the symbols are redefined. The original sequence \( x_r^{(0)} \) is represented as \( x(t) \), the sequence \( x_r^{(i)} \) generated by one accumulation is denoted as \( y(t) \) and the prediction result \( x_r^\ast(t) \) is denoted as \( z(t) \).

The expression of the differential equation of gray neural network model with \( n \) parameters is

\[
\frac{dy_i}{dt} + ay_i = b_1y_2 + b_2y_3 + ... + b_{n-1}y_n
\]

In the formula, \( y_1, y_2, ..., y_n \) is the system input parameter; \( y_1 \) is the system output parameter; \( a, b_1, b_2, ..., b_{n-1} \) is the differential equation coefficient. The formula in the time response is

\[
z(t) = y_1(0) - \frac{b_1}{a}y_2(t) - \frac{b_2}{a}y_3(t) - ... - \frac{b_{n-1}}{a}y_n(t) + \frac{b_1}{a}y_2(t) + \frac{b_2}{a}y_3(t) + ... + \frac{b_{n-1}}{a}y_n(t)
\]

\[
d = \frac{b_1}{a}y_2(t) + \frac{b_2}{a}y_3(t) + ... + \frac{b_{n-1}}{a}y_n(t)
\]

\[
f(t) = \frac{b_1}{a}y_2(t) + \frac{b_2}{a}y_3(t) + ... + \frac{b_{n-1}}{a}y_n(t)
\]

In the figure, \( t \) is the input parameter number; \( y_2(t), ..., y_n(t) \) is the network input parameter; \( w_{i1}, ..., w_{in} \) is the network weight; \( w_{in} \) is the network prediction value; LA, LB, LC and LD represent the four layers of the gray neural network respectively. The process of forecasting greenhouse gas emissions based on gray neural network is shown in the figure 2.
Among them, gray neural network constructs input / output data dimension to determine gray neural network structure. We take carbon dioxide emissions, methane emissions and global forest cover as input indicators and atmospheric temperature as output indicators, so we establish a 1-1-4-1 gray neural network structure. Therefore, there is 1 node in the LA layer and 1 node in time series t and LB and 4 nodes in LC. The 2-4 inputs the normalized data of CO2 emission, methane emission and global forecast of forest cover area respectively [6]. The output is as atmosphere temperature.

3. Atmospheric Temperature Prediction Model Based on Gray Neural Network

3.1. Data collection and processing
In the World Bank database, the annual carbon dioxide emissions, methane emissions and global forest cover data from 1990 to 2012 are collected [7]. There are differences between the unit and the magnitude of the three indicators. Therefore, we consider the non-dimensional treatment. In this paper, "efficacy coefficient method" is used to eliminate dimension, the formula is

\[ X^*_j = c + \frac{x_j(t_k) - m_j(t_k)}{M_j(t_k) - m_j(t_k)} \times d \]

Here, \( X^*_j(t_k) \), \( x_j(t_k) \) represents respectively the original observed value and the dimensionless processed value of the th index of the jth evaluated object at time \( t_k \); \( M_j(t_k) = \max \{x_j(t_k)\} \)

\[ M_j(t_k) = \min \{x_j(t_k)\}; \quad c \text{ and } d \text{ are known normal numbers. The purpose of } c \text{ is to "translate" the transformed values. The effect of } d \text{ is to "zoom in" or "zoom out" on the transformed values.} \]

Table 1. Global carbon dioxide, methane, forest area data

| Time  | CO₂ emissions (kt) | Methane emissions (kt of CO₂ Equivalent) | Forest area (sq.km) |
|-------|-------------------|-----------------------------------------|---------------------|
| 1990  | 22149402          | 6668380                                  | 41282695            |
| 1991  | 22403929          | 6708550                                  | 41210028            |
| 1992  | 22183417          | 6846520                                  | 41137360            |
| 1993  | 22162175          | 6503170                                  | 41064693            |
| 1994  | 22551691          | 6617590                                  | 40992026            |
3.2. Establish GM (1,1) model predictive index value

The GM (1,1) model was established based on the data of global carbon dioxide and methane emissions and forest area from 1990 to 2012, and the predicted values of the three indicators from 1990 to 2012 were respectively obtained[8]. Table 2 shows the GM (1,1) Predict the three indicators from 1990 to 2012.

| Years | CO\textsubscript{2}/10\textsuperscript{7} t | CH\textsubscript{4}/10\textsuperscript{6} t | Forest area/10\textsuperscript{6} km\textsuperscript{2} | Post-test difference |
|-------|--------------------------------|---------------------------------|---------------------------------|---------------------|
| 1990  | 3.671                           | 6.668                           | 4.128                           | 0.1030              |
| 1991  | 3.764                           | 6.331                           | 4.112                           | 0.2726              |
| 1992  | 3.859                           | 6.398                           | 4.017                           | 0.0653              |
|       |                                 |                                 |                                 |                     |
| 2010  | 3.320                           | 7.731                           | 4.010                           |                     |
| 2011  | 3.405                           | 7.813                           | 4.005                           |                     |
| 2012  | 3.491                           |                                 | 3.999                           |                     |

Prediction results of the three indicators Posterior difference test C =0.1030,0.2726,0.0653 are less than 0.35. This shows that the model accuracy level is excellent.

3.3. Neural network simulation output

Taking the predicted value of the three indicators from 1990 to 2012 as the input of the model of artificial neural network and the measured value of global average temperature from 1990 to 2012 as the output and a random number between 0-1 of the network weight and the threshold, Train the network and get a series of weights and thresholds corresponding to the nodes in the network[9]. Then, the forecast value of GM (1,1) model for 2013-2032 is taken as the input of neural network, and the neural network simulation is used to get the output value as follows:

| Years | Predictive value | Years | Predictive value |
|-------|------------------|-------|------------------|
| 2013  | 14.675           | 2028  | 14.941           |
| 2014  | 14.692           | 2029  | 14.957           |
| 2015  | 14.708           | 2030  | 14.975           |
| 2016  | 14.741           | 2031  | 14.991           |
| 2017  | 14.757           | 2032  | 15.008           |

Gray neural network training process shown in Figure 3:
As can be seen from the figure, the gray neural network converges very fast, with an average prediction error of 7.21%, indicating a high degree of confidence in the prediction [10]. Combined with the 2013-2032 projections and the measured values from 1960 to 2012, the global average temperature table for every 10 years from 1960 to 2032 is available.

| Years | Temperature | Years | Temperature | Years | Temperature | Years | Temperature |
|-------|-------------|-------|-------------|-------|-------------|-------|-------------|
| 1960  | 13.96       | 1970  | 14.04       | 1980  | 14.23       | 1990  | 14.39       |
| 2000  | 14.41       | 2010  | 14.67       | 2020  | 14.81       | 2030  | 14.98       |

4. Conclusion
From the figure, this paper sets out the forecasting model of gray neural network based for the purpose of improving global annual average temperature forecasting accuracy. The model has better fitting and forecasting ability. From the table, since 1960, the global average temperature has been on the rise every 10 years. It is an inevitable trend to show that global warming is caused by the "1-1-4-1 gray neural network structure." The rise in temperature is caused by industrial fossil fuel Combustion, reduction of forest area resulting in synergy.
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