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Research on the Prediction of Carbon Emission Based on the Chaos Theory and Neural Network

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Abstract: *In this paper, carbon emissions and the related problems are studied based on carbon emission time series data and the chaos theory, in order to make clear the relationship among the data, and we reconstruct the time series by phase space reconstruction. Finally, the predicting model of the carbon emission is established with BP neural network. The simulation results show that the hybrid of chaos theory and BP neural network can be used to fit and predict the carbon emissions time series without considering other factors, which is easier and more accurate than other predicting method.*

Keywords: *Carbon emissions, Chaos theory, BP neural network, Phase space reconstruction.*

Introduction

Since 21st century, the global climate has been getting deterioration, and because of the greenhouse effect, massive emissions of greenhouse gases, especially CO_2, exacerbate the pace of global warming, inducing extreme weather, species extinction and desertification, the relevant departments has made investigation and the report is that: human makes impact on the climate system, and this effect keeps increasing in all continents of the world with in a variety of observed effects. Since the end of 21st century [27], the global average surface warming is mainly caused by the cumulative CO_2 emissions. Since industrialization, CO_2 concentration has increased by 40%. As a responsible big country, in November 2014 China made the commitment in “Sino US Joint Declaration on climate change” to reach the peak of carbon dioxide emissions and strive to reach the peak as soon as possible in 2030. Controlling and reducing carbon emissions has become an inevitable choice, and forecasting the global hereafter carbon emissions in different countries is one of the important basis of emission reduction targets, the carbon emission has become a hot issue of academic research.

Study on the influencing factors of carbon emissions and predict began in 1970’s, mainly from two aspects: one is the influence factors of carbon emissions, which means establishing model to predict the carbon emissions based on the relationship between carbon emissions and its influence factors. Most studies are based on the IPAT equation [8] and Kaya [15] the identity of carbon emissions to establish improved STIRPAT model, which is the mainstream analysis tool [4, 7, 16, 23] technology in recent years, and some scholars use the gray relational analysis, neural network and clustering analysis to do predict [11, 17, 28, 29] on carbon emission in china. The other one is a hybrid model, which establish hybrid energy input-output economic model of carbon emissions by considering the relationship between the environment and the GDP, energy consumption, energy structure, technology and other factors of the construction sector [2, 3, 6, 14, 22, 25]. The influence factors of carbon emissions have complexity and diversity for the researchers.

In recent years, domestic and scholars have carried out researches on the time series data in different areas, such as astronomy, meteorology and economics, and proved the its own chaotic characteristics, that is: in nature system, especially the open, far from equilibrium, nonlinear system [18], There is probably chaos phenomenon. Although the application of chaos theory in economics is very extensive, the existing carbon emissions prediction research does not take into account the chaos characteristics of the carbon emissions data combined with machine learning for the simulation and prediction of machine learning, which can find potential internal links directly from the data without specific assumptions. We combined chaos theory and neural network in this field for prediction of carbon emissions in the world A new method and idea: making reconstruction of carbon discharge time series by means of phase space reconstruction through the analysis of chaos of carbon emissions data without considering other factors, then exploring the related rules about the chaotic attractor, which can effectively describe the existing data, fitting and making the prediction of data using BP neural network, chaos theory and neural network fusion.

Chaos identification of carbon emission data

Chaos is a kind of special form of nonlinear dynamics system, chaotic phenomena usually appear in the deterministic system, which has irregularity and randomness, and the premise of carbon emission prediction by chaos theory is that the carbon emissions data is chaotic. From a scientific point of view, pure random and pure chaos are ideal, but many of the actual time series contains a certain randomness in practice, as well as the existence of certain. Therefore, for the nature of the carbon emission time series data, it is more reasonable to explore the issue of carbon emissions under condition that its chaos is mainly in a certain degree of confidence, in order to ensure its chaotic time series.

An important feature of chaotic system is that it has the chaotic attractor. For any system, the decision of whether the chaos exists usually need to focus on the chaotic attractor, through the analysis of the of the two basic characteristics [12, 13]: the first one is to judge that the attractor's whether its fractal dimension has self similarity or not; the second is to consider whether or not it has initial value sensitivity. If the system is in accordance with the above requirements, then it is a chaotic attractor, so is system. In order to grasp the nature of the time series more accurately and comprehensively, we usually start from two angles, namely: the qualitative analysis and the quantitative analysis. The former is fuzzy, only roughly analyzing the time series properties in the time domain or frequency domain, such as phase diagram, Poincare section method, and stroboscopic sampling method [18]. This method does not require complex calculations, but the main disadvantage is that the judgment is not accurate. The other one's analysis is accurate with the help of different methods and indicators, such as: Kolmogorov entropy [30], the largest Lyapunov exponent [20] and correlation dimension, thus it can accurately describe the chaotic system. The quantitative method is superior to the qualitative analysis method on the accuracy, but this kind of method has the disadvantages such as complex calculation process and so on. The key of chaos identification is to apply a variety of methods to confirm and complement each other.

Phase space reconstruction

The phase space reconstruction of nonlinear time series is a prerequisite for the analysis of chaos. Packard et al. proposed the method of phase space reconstruction in 1980 [19], and Takens laid a solid foundation with mathematics for it 1981 [26]. The research chaotic dynamics results show that the system components are realized with the aid of other component evolution, therefore, one component can be the object of the study , when grasp its time series data, the original system get extraction or recovery. Scholars treat the original system as the research object, using delay coordinates of a variable to realize the phase space reconstruction, and then they use the fixed time delay point observations to treat it as a new dimension, finally the phase space is constructed. Compared with the original system, the two have equivalence and similarity. The scholars have pointed out that by the research of topological equivalence, the recovery of the attractor characteristics can be promoted [26]. Suppose that the time series is $\{x(t), t=0,1,2,\cdots,n\}$, and integrate it into R^m to make the reconstructed phase space be $\{X_i, i=0,1,2,\cdots,N\}$. In the space:

$$X_1=(x(1), x(1+\tau), \cdots, x(1+m\tau)),$$
$$X_2=(x(2), x(2+\tau), \cdots, x(2+m\tau)),$$
$$\ldots\ldots$$
$$X_N=(x(N), x(N+\tau), \cdots, x(N+m\tau)). \tag{1}$$

In this formula, the delay time is τ, m is the embedding dimension, N is the sum of the phase points, $N=n-(m-1)\tau$ and X_i are reconstructed phase space, $i=0,1,2,...,N$.

Time of delay

In the phase space reconstruction, the most important parameter is the time of delay, and the following principles should be followed in the selection process: the selected $x(i)$ and $x(i+\tau)$ should be characteristic of independence as well as relevance. The most reasonable delay time should not be too large or too small, if too small, $x(i)$ and $x(i+\tau)$ will be too close, so it is difficult to effectively distinguish the two. In practice, it is difficult to obtain the corresponding independent coordinates, meanwhile the attractor reconstruction is very close to the diagonal of phase space, thus in the reconstruction phase space when information is not clear under the premise, the redundant error will appear probably; if it is too large, the coordinates will get obvious randomness in the reconstruction, and the attractor track will overshadow in two completely different direction, then the original power system will make the signal distortion of reconstructed vector which can not reflect the true evolution rules of trajectories in phase space.

On the selection of delay time τ, a delay time and the embedding dimension m are not correlated with each other, the specific methods are self correlation method [18], mutual information method [10], complex autocorrelation method [18] and mean displacement (AD) method [24]. Some scholars believe that the above two factors are closely related, the method has time window method [21] and C-C method [9]. But according to the practice, in order to reduce the computational difficulty and make it more simple and easy, scholars are very concerned about the autocorrelation function method and the average mutual information method, taking the self correlation method as an example:

The chaotic time series is $(x(t_1), x(t_2), ..., x(t_n))$, the auto correlation function of time span $j\tau$ in $\{x(t_i)\}$ is:

$$R_{xx}(j\tau) = \frac{1}{N}\sum_{i=0}^{N-1} x(t_i)x(t_{i+j\tau}) \tag{2}$$

j is static, we can get the function of the image about the time τ (that is τ = 1, 2, ...). When the autocorrelation function declines to initial value $1-\frac{1}{e}$, the time t is the best delay time τ.

Embedding dimension

Assuming the attractor fractal dimension of the original system is D, the embedding dimension is m, according to the Takens theorem, as long as $m \geq 2D+1$, the geometry structure of power system can be fully open [26], but $m \geq 2D+1$ is only sufficient condition. Scholars pointed out that the m value's range is (D, 2D + 1) [24]. For the system, the m value is very important in the reconstruction of embedding dimension, if the value is too small, it is difficult to fully open the attractor, and if the value is too large, the observations have a greater demand, so is the difficulty of calculation. At present, the most common methods are the following: false neighboring method [18], singular value decomposition method [1], Cao method [5] and so on, but the advantages and disadvantages of these methods are different, taking the saturated correlation dimension method as an example:

The complexity of attractor in phase space is measured by correlation dimension, in which embedding dimension and correlation dimension was positively related, if the former is increased, the correlation dimension of random sequence will continue to increase, and the chaotic sequence will also be close to the fixed value. The correlation dimension has simple calculation, conservative and stable characteristics. Scholars use the embedding theory and the phase space reconstruction to put forward a new algorithm, that is: from the perspective of time series, making a direct calculation of the correlation dimension, and this method is called the saturated correlation dimension method (GP algorithm). The method can not only calculate the embedding dimension, but also can distinguish whether the given time series is chaotic or random according to whether the correlation dimension is saturated.

Considering a pair of phase points in the phase space of M:

$$\begin{aligned} X(t_i) &= (x(t_i), x(t_{i+\tau}), \cdots, x(t_{i+(m-1)\tau})) \\ X(t_j) &= (x(t_j), x(t_{j+\tau}), \cdots, x(t_{j+(m-1)\tau})) \end{aligned}. \tag{3}$$

Set the Euclidean distance between them as $r_{ij}(m)$:

$$r_{ij}(m) = \left\| X(t_i) - X(t_j) \right\|. \tag{4}$$

The critical distance is r, the correlation integral $C(r, m)$ is the ratio of the point logarithm, the distance is less than r:

$$C(r, m) = \frac{1}{N(N-1)}\sum_{i \neq j} H(r - \| X_i - X_j \|), \tag{5}$$

Where N is the total number of points, H(.) is the Heaviside function

$$H(x)=\begin{cases}1 & x>0\\ 0 & x\le 0\end{cases},\tag{6}$$

$C(r, m)$ is the probability that the distance between two points in phase space is less than r, for a cumulative distribution function, it describes the degree of phase point $x(t)$ in the phase space of a point r, the underlying relationship:

$$\lim_{m\to\text{saturation}} C(r,m)\propto r^D,\tag{7}$$

D is the correlation dimension, which value is:

$$D=\lim_{m\to\text{saturation}}\lim_{r\to 0}\frac{\ln C(r,m)}{\ln r}.\tag{8}$$

If the given system is chaotic, when the phase space dimension m reaches a certain value, the correlation dimension is in a constant state, and the saturated correlation dimension represents the fractal dimension of the attractor in the dynamic system, in which the m is the optimal value. However, the method also has some disadvantages, the most serious one is the large amount of calculation, and it is difficult to determine the critical distance, therefore, researchers have put forward a lot of improvements for it.

Prediction model based on Hybrid chaos theory and BP neural network

Set $\{x(t), t=0,1,2,\cdots,n\}$ as the time series of carbon emission, set τ as the optimal delay time and the best embedding dimension as m, then the reconstructed phase space is:

$$\{X(t)\mid X(t)=[x(t), x(t+\tau),\cdots, x(t+(m-1)\tau)], t=0,1,2,\cdots, n-(m-1)\tau\}.\tag{9}$$

According to F. Takens theory, the smooth mapping $f:R^n\to R$ accords with conditions below [7]:

$$x(t+m\tau)=f(X(t))=f(x(t), x(t+\tau),..., x(t+(m-1)\tau)).\tag{10}$$

Assuming that the relevant equation of projection f or formula is given, then we can get an effective prediction of carbon emissions by combining the inherent regularity of carbon emission time series. But it is difficult to directly solve the related functional equations at present. The reason is that the chaotic dynamics model of time series is too complicated, and there is a certain nonlinear relationship. BP neural network has a certain particularity, it has remarkable achievements in processing information. Therefore, it has been highly concerned by people in all fields. Its specific characteristics are: the ability of nonlinear mapping, self-learning ability, self organization, parallel architecture, parallel processing of information, using the prediction of time series, ability to bear strong noise in the data which other methods cannot compare with.

Based on this, scholars establish a prediction model, the steps are: use BP neural network model and construct the Eq. (10), then use neural network to calculate, that is: predict the next value $x(t+\tau)$ by m numerical value sequence $(x(t), x(t-\tau),..., x(t-(m-1)\tau))$, and it is a structure of BP neural network to fit $m-p-1$ or function approximation:

$T(x(t)) = f(x(t), x(t-\tau), ..., x(t-(m-1)\tau))$.

Finally, we can predict the chaotic time series data through the training model.

Carbon emission prediction

In this paper, the data are from the world bank public data (http://data.worldbank.org.cn/), the world bank public database lists more than 7000 indicators of the world bank database, which can be browsed in accordance with national, index, and thematic data directory. We downloaded the more than and 200 countries and regions around the world carbon dioxide emissions from 1960 to 2011, which contains carbon dioxide emissions data sequence of a country or a region from 1960 to 2011, and we select the 47 data to make up the training sample set, the remaining data are treated as test samples after the structure optimization and the adjusted parameters in order to meet the simulation forecast. Most studies are on Japan, Britain, China, East Asia and the Pacific (all income levels) and some low income countries' carbon emissions data, take China for example, the delay time of auto correlation method is 5, and the maximize Lyapunov index is 0.067 with a small amount of data, if the index is positive, it means the chaotic attractor, so the system is the chaotic system. By self correlation method, the delay time is 5 as shown Fig. 1.

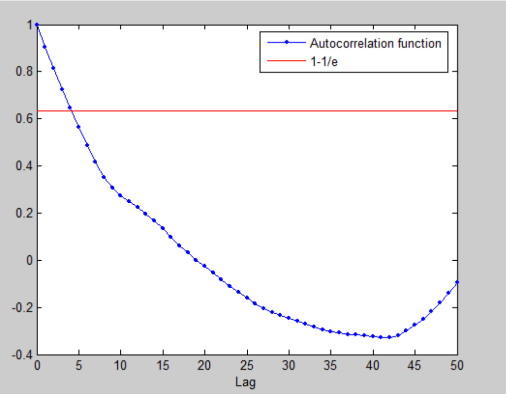

Fig. 1 Auto correlation function

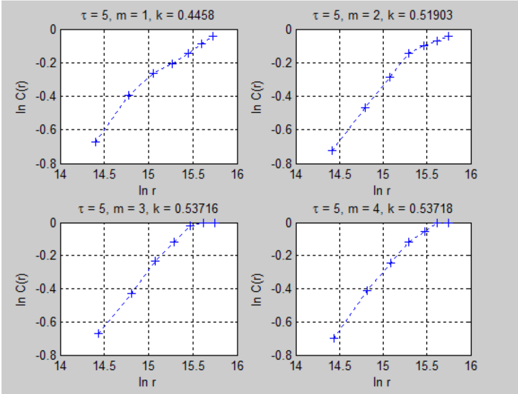

Fig. 2 Correlation dimension

The delay time is 5, and the correlation dimension is calculated by GP algorithm. When the m is 3, the slope (correlation dimension D) is no longer increasing as far as 0.54, and the time series proves a chaotic sequence again. So we think that the correlation dimension of D is 0.54, according to the theory of Takens, as long as $m \geq 2D+1$, the geometric structure of power system can be fully opened, so the embedding dimension is 3, therefore, build a BP neural network excitation function using Sigmoid function 3 input and 1 output, the number of hidden layer is 8 after training and the global error is less than 5%, the fitting data such as image is shown in Fig. 3.

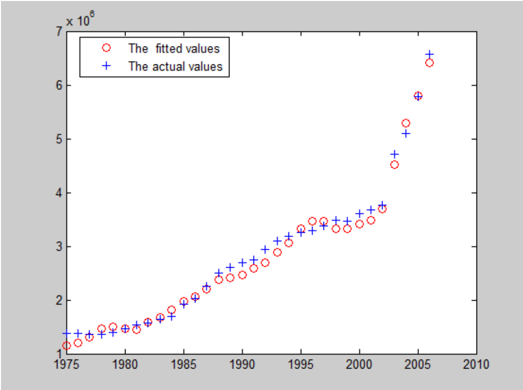

Fig. 3 China carbon emission fitting data

So far, there is not a scientific method to determine the hidden nodes. We take the hidden nodes is 3, 4, 5, 6 and 10 to do fitting once again, the mean value result is good, of which the reason is that the network is small, only 3 input and 1 output, 50 groups of insufficient training data, the number of nodes in hidden layer does not affect the basic training and the prediction results. In order to compare the results, we use the same set of data with the ARIMA model and gray theory to fit and predict the effect of BP neural network, and find it better than these two models, the specific data see Table 1.

Table 1. 2007-2011 test results of China's carbon emission data

Year	**China carbon emission data, [thousand tons]**	**ARIMA model**		**Gray theory**		**Model of this paper**	
		Predicted value	**Error %**	**Predicted value**	**Error %**	**Predicted value**	**Error %**
2007	6791805	7178055	5.687	6566792	-3.313	7023745	3.415
2008	7035444	6724759	-4.416	6743754	-4.146	7286902	3.574
2009	7692211	8121975	5.587	8003976	4.053	7959925	3.48
2010	8256969	7748753	-6.155	7900846	-4.313	8601177	4.169
2011	9019518	8611656	-4.522	8591452	-4.746	8789491	-2.55

In the same way, we trained and predicted carbon emissions data in the world, Japan, Britain, Chinese, East Asia and the Pacific (all income levels) and some low income countries, and achieved good results, the prediction results of world carbon emissions are listed in Table 2.

From the above analysis, we get good fitting effect by hybrid of chaos theory and BP neural network prediction model, and we can make the correct short-term forecast for the world's carbon emission data.

Table 2. 2007-2011 world carbon emission data prediction test results

Year	World carbon emission data, [thousand tons]	ARIMA model		Gray theory		Model of this paper	
		Predicted value	Error %	Predicted value	Error %	Predicted value	Error %
2007	31286844	32440077	3.686	29924928	-4.353	29936689	-4.315
2008	32049580	33830992	5.5583	30559916	-4.648	30888128	-3.624
2009	31902900	30495025	-4.413	33387342	4.653	31687469	-0.675
2010	33516380	31788946	-5.154	33036090	-1.433	32442559	-3.204
2011	34649483	36545503	5.472	33351167	-3.747	33019019	-4.706

Conclusions

In this papers, we did research on the prediction of carbon emissions with consideration of complexity and diversity, so far, no method shows that which factors are the most appropriate, through the identification of showed a chaotic characteristics in carbon emissions data, we used the method of phase space reconstruction fusion, BP neural network to establish prediction model, and this method has good prediction ability and good generalization ability. Compared with other methods, this method does not need to consider other factors, providing a simple model which is convenient and efficient for carbon emissions forecast in the world.

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