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Power Load Forecasting based on the Parallel Chaos Algorithm

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The power load forecasting is an important part of the power system planning and the operation research. With the continuous increase of the power consumption in China, the research of the power load forecasting has been paid by the people. Because the power load data are very huge, it brings many difficulties to the related prediction research. In this paper, we use the idea of the parallel algorithm to deal with the massive power load data and we propose the improved parallel chaos prediction method to study the power load forecasting. The experimental results show that the algorithm not only can reduce the prediction time but also can improve the prediction performance. In addition, the prudential results are more accurate.

1. Introduction

The power load forecasting is the strategies prediction of the power system. It is the premise (Ömer, 2016) to ensure the reliability and the economic operation of the power system. With the continuous development of the power network management, the power network management needs to be modern and scientific. In addition, we need to improve the processing speed of the power load data and strengthen the component of the computer technology in the power loading forecasting (Martinez-Anido et al., 2016).
From the point of the view of the spatial load, the factors that affect the fluctuation of the urban electric power load are mainly determined by the change of the land use and the load density of the unit data. Therefore, the lower forecasting model based on the change of the land use and the risk analysis of the load density is proposed that considered the influence of the risk factors on the change of the load density (He et al., 2015). The importance of Short-Term Load Forecasting (STLF) in power systems planning and management is reflected by the plethora of the related researches. Therefore, the lower load forecasting model which is based on the artificial neural networks (ANNS) is developed. The hybrid forecasting models were characterized by high level of parameterization and efficiency (Panapakidis, 2016). It is very necessary that the more accurate and stable load forecasting model in the field of the power load forecasting. Therefore, a new combined model is applied. At the same time, a new optimal algorithm optimizes the parameters of the combined model. The model predicted the power load data of New South Wales, the State of Victoria and the State of Queensland in Australia and achieved the good effect (Xiao et al., 2016). Some scholars put forward the short-term load forecasting methods based on the wavelet transform, the extreme learning machine and the partial least square regression. The method introduced the integration test of the wavelet into the prediction model. Then, it decomposed each sub-component and predicted separately the wavelet. Then, it used the partial least squares regression method to combine. The numerical results showed that the proposed method can significantly improve the prediction performance (Li et al., 2016).
The power load forecasting has the special significance for the power system. It is related to the livelihood of the people. In this paper, we propose an improved parallel chaos algorithm to forecast the power load. The experimental results show that the algorithm is reliable and effective. The structure of this paper is as follows. The first part is introduction. In this part, we introduce the background knowledge of the power load forecasting. The second part is the prediction theory of the chaos algorithm. The third part is the improved parallel chaos prediction algorithm. In this part, we use the idea of the parallel computing to improve the chaos algorithm. The fourth part is the experiment and the fifth part is the conclusion.

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2. Chaos algorithm

Chaos is a similar random and seemingly random phenomenon in the deterministic nonlinear system. There is a certain order in this seemingly random act. It is mainly to study the uncertainty caused by internal nonlinearity of the system (Akhmet et al., 2014). If an irregular phenomenon can be identified as belonging to the chaos, at least from the principle of speaking, the change will have certain regularity (Liang and Kang, 2016). Therefore, in the chaotic system, the system is very sensitive to the initial value. That is, if the initial value has a small change, the results of the long-term evolution will be a great difference (Farshidianfar and Saghafi, 2014). Chaotic system will show great randomness. Therefore, it is impossible to predict the chaotic system in a long term. However, it can be accurately predicted in the short-term.

Theorem 1: We assume that *f* is the continuous self-mapping in interval [*a,b*]. If *f(x)* has three periodic points, *f(x)* has *n* periodic points for any positive integer *n*.

Definition 1: If **the** continuous mapping *f* in the closed interval [*a,b*] meets the following three conditions:

(1) For any natural number *k*,

$$x_k \in [a,b] \tag{1}$$

Then,

$$f_k(x_k) = x_k \tag{2}$$

That is, there exists the periodic point of arbitrary order.

(2) For the non-number set $S \subset [a,b]$, it has no the periodic point in the set *S*. For any $x, y \in S$, there is,

$$\lim_{n\to\infty}\inf \left| f^n(x) - f^n(y) \right| = 0 \tag{3}$$

$$\lim_{n\to\infty}\sup \left| f^n(x) - f^n(y) \right| > 0 \tag{4}$$

(3) For any $x, y \in S$, there is,

$$\lim_{n\to\infty}\sup \left| f^n(x) - f^n(y) \right| > 0 \tag{5}$$

We call that f is the chaos in the interval $[a,b]$.

Takens Theory: If M is d dimension manifold. $\phi : M \to M$. φ is diffeomorphism. $y : M \to R$ and y has a continuous second order derivative. $\phi(\varphi, y) = M \to R^{2d+1}$,

Where

$$\phi(\varphi, y) = y(x), y(\phi(x)), y(\phi^2(x)), \cdots, y(\phi^{2d}(x))) \tag{6}$$

Then, $\phi(\varphi, y)$ is a imbedding from M to R^{2d-1} .

According to the Takens principle, the state that the phase point X_n moves to X_{n+1} can be determined by X_n and the previous phase point (El-Shorbagy et al, 2016). Therefore, there is the following function relation.

$$X_{n+l} = F(X_n) \tag{7}$$

Where, l is the prediction time. F is the prediction function. The above formula is the established chaos forecasting model. According to the known data sequence, we can estimate the prediction function F . According to the length of the forecast time, it can be divided into one step prediction and multi-step prediction.

The one step prediction is as follows.

$$\widehat{X}_{n+1} = F(X_n) \tag{8}$$

The k steps prediction is as follows.

$$\widehat{X}_{n+k} = F(X_{n+k-1}) \tag{9}$$

Where

$$\widehat{X}_{n+k-1} = (\widehat{x}_{n+k-1}, \widehat{x}_{n+k-1+\tau}, \cdots, \widehat{x}_{n+k-1+(m-1)\tau}) \tag{10}$$

Therefore, if we solve the one step prediction, the k steps prediction can be deduced.

3. Improved parallel chaos prediction algorithm

Firstly, it is the choice of the delay time τ.

The delay time τ is an important parameter in the theory of the chaos prediction. Its value cannot be too large or too small Elena (2014). If the value of τ is too small, the difference of the coordinate in the reconstructed phase space is very small. If the value of τ is too big, the coordinates in the reconstructed phase space are independent of each other. This paper assumes that

$$C_t(\tau) = \frac{\sum_{1}^{n-\tau}(x_{n+\tau} - \overline{x})(x_n - \overline{x})}{\sum_{1}^{n-\tau}(x_n - \overline{x})^2} \tag{11}$$

When $C_t(\tau)$ is the first time to down to $1/e$, τ is the nearest delay time interval.

The second is the choices of the correlation coefficient D and the embedding dimension m.

The correlation function is an effective way to find out the correlation dimension. It represents the probability that the distance between any two points on the attractor in the phase space is less than r.

$$c(r) = N_1(r)/N(r) \tag{12}$$

$N_1(r)$ is the number that the distance of each point is less than r. $N(r)$ is the total points number. For any point y_i and y_j in m dimension phase space,

When

$$\left|y_i - y_j\right| > \tau \tag{13}$$

The distance of the two points is,

$$r_{i,j} = \left|y_i - y_j\right| \tag{14}$$

For all $y_i, i = 1, 2, \cdots, N_m$, we repeat this process and get another expression of the correlation function.

$$C(r) = \frac{1}{N(N-1)} \sum_{i}^{N} \sum_{j}^{N} \theta(r - r_{i,j}) \tag{15}$$

Where, $\theta(x)$ is the Heaviside function.

$$\theta(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{16}$$

Obviously, the calculation result of $C(r)$ is related to the value of r. If r is too big, $D = 0$. It indicates that the useful signal in the system will be submerged. If r is too small, the all accidental noise in the experiment will be performance compared with the useful signal. The value of r is not related to the internal nature of the system. Therefore, we must adjust the range internal of r. After we select the appropriate value r, in the internal, it will have,

$$C(r) = r^D \tag{17}$$

Therefore,

$$D = \lim_{r \to 0} \frac{InC(r)}{Inr} \tag{18}$$

Then, we gradually increase the embedding dimension and compute each embedding dimension which corresponds to the correlation dimension value. When the correlation dimension is not changed, the corresponding minimum embedding dimension is the embedding dimension of the system.
Through the carrier method, the chaotic state can be mapped to the optimization variables and can make the ergodic range of the chaotic motion amplify to the range of the optimization variables. After that, we use the chaotic variables to search and form the chaotic search.
The choice of the chaotic dynamics equation is Logistic mapping.
Where, _ is the control variable. When $\_ = 4$, the system is into the chaos state. The input of the system is in $(0,1)$. The output is also in $(0,1)$. The output has the ergodic property and any state will not be repeated.
The chaotic motion has the ergodicity in certain range. However, because the chaos system has the dependence of the initial value, some states may take longer time to achieve. If the global optimal value happens to be in these states, the search time will be longer. From several different initial points, this paper begins to do the parallel computing in order to reduce the sensitive dependence on the initial conditions of the chaotic system and speed up the search in the search. When the research achieves a certain extent, we do the second carrier and find out the optimal solution as soon as possible. Therefore, we apply the ideal of the parallel into the chaos algorithm. The steps are as follows.
The first step is to initialize the algorithm.
We set $n = 1$. n is the number of iterations of the algorithm.

$$x_{(i,j,n+1)} = 4 \cdot x^2{}_{(i,j,n)} \big/ (x_{(i,j,n)} + 1) \tag{19}$$

Where, $i = 1, 2, \cdots, p$. It shows that there are i groups different initial starting points. Where, $j = 1, 2, \cdots, N$. It shows that the number of variables that the optimized problem $\min f(x)$ contains.
The second step is to do the first carrier.
We introduce the $x_{(i,j,n+1)}$ into the optimization variables. At the same time, according to the range of each optimization variable, we enlarge the range of change of the chaos variables into the range of the corresponding optimal variables.

$$x''_{(i,j,n+1)} = c_{(i,j)} + d_{(i,j)} \cdot x_{(i,j,n+1)} \tag{20}$$

Where, $x_{(i,j,n+1)}$ is the chaos variable, $c_{(i,j)}$ and $d_{(i,j)}$ are the constants. They are also the multiple of magnification. $x'_{(i,j,n+1)}$ is the variable of the optimized problem $\min f(x)$.
The third step is to do the iterative search.
We begin the iterative search. The optimal value that obtains in the chaos variables is the current optimal value.

$$f_n^* = \min(f_{(1,n)}, \cdots, f_{(i,n)}, \cdots f_{(k,n)}) \tag{21}$$

After the iteration, if it does not search the better optimal solution, we need to make the second carrier according to the following function.
$T \cdot x_{(j,n+1)}$ is the small chaos variable in the ergodic interval. T is the adjustment constant. $x^*{}_{(i,j)}$ is the current optimal solution.
The fourth step is continue to do the second carrier iterative search. When it Satisfies the number of the M iteration, if it does not have the better optimal solution, it will stop to research and output the current optimal value.

4. Experiment

In this paper, we select the power load data of the province of East China power grid enterprise. The scope of the training data is the electricity data from November 15, 2013 to November 25, 2013. The sampling interval for each device is 15min. Firstly, We analyze the performance of the improved parallel chaos algorithm and the results are shown as follows.

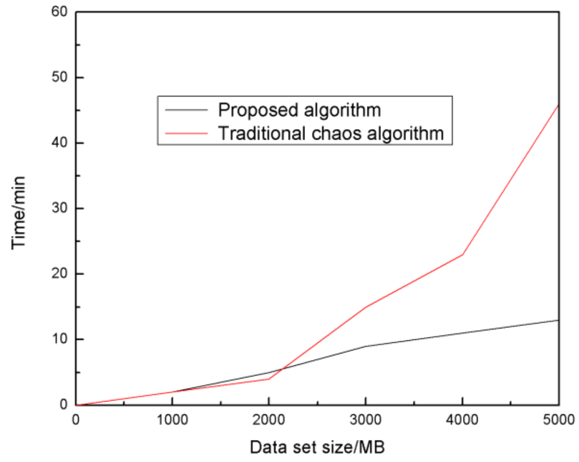

Figure 1: Consume time contrast between the traditional chaos algorithm and the proposed algorithm

Form the results of the figure 1, we can see that the forecasting time has little difference in the small sample data. On the contrary, the needed time of the traditional chaos algorithm is slightly superior to the proposed algorithm. It has some reasons. In the small data, the proposed algorithm will still divide the data into several sub samples. The communication cost among different data sub samples will increase and impact the prediction speed. However, with the increase of the sample set, the iteration time that the forecasting algorithm needs has the significantly different. The needed time of the proposed algorithm is much smaller than the traditional chaos algorithm.
After that, we compare the predicted value with the actual value and the results are shown in Figure 2.

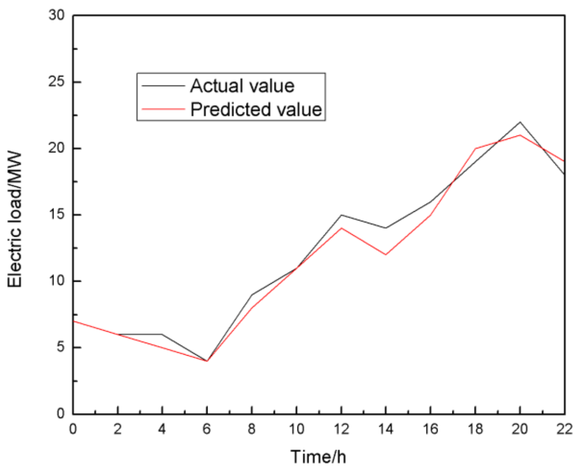

Figure 2: Electric load predicted contrast curve

From the figure 2, we can see that the curve of the predicted value and the actual value is similar. It indicates that the prediction method has good prediction effect. Figure 1 and Figure 2 illustrate the proposed algorithm has the effectiveness and reliability.

5. Conclusion

With the development of the national economy and people's living standards improve, People's demand for power quality is higher and higher. The power load forecasting is as a basic tool to ensure the quality of electric energy. Its importance is more and more recognized by people. At the same time, the power load forecasting is a complicated work with the heavy workload. In this paper, according to the characteristics of the power load forecasting, the paper introduces the idea of the parallel operation and puts forward the improved parallel chaos prediction method. After that, we make a numerical analysis of the method. The main work of this paper is as follows. Firstly, this paper introduces the research background of the power load forecasting. Secondly, this paper proposes an improved parallel chaos prediction algorithm. Thirdly, this paper applies this method to forecast the power load. The experimental results show that the algorithm is effective and reliable.

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