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Design of Power Quality Steady State Index Evaluation System under the Background of Big Data

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Abstract

In order to further optimize the operation mode of China's power grid and improve the quality of power supply in the grid, in this study, according to the non-periodic and periodic characteristics of the steady state index of power quality, a power quality steady-state index evaluation and prediction system based on chaotic system theory and least squares support vector machine (LSSVM) in large data background is designed. First, Firstly, chaotic system theory is used to reconstruct the phase space of the historical data of classical power quality steady-state indices, and to construct a new data information space covering attractors. Then, the LSSVM is used to train the samples in high-dimensional space, and the particle swarm optimization (PSO) algorithm is used together to get the best index evaluation and prediction system model. At the same time, the system is applied to the actual monitoring of the electric energy treatment capacity of a distribution network in a certain place. The typical steady-state index of power quality is used to evaluate and monitor, and the average relative error is less than 7%. Obviously, the result is better than the traditional back propagation (BP) neural network prediction method, which proves that the power quality steady-state index evaluation system based on chaotic system theory and least squares support vector machine under large data can be widely used.

Keywords: *chaotic system theory; power quality steady state index; large data; support vector machine*

1. Introduction

With the rapid development of China's economy and the continuous improvement of science and technology, great and significant changes have taken place in the characteristics of power grids, load composition and control techniques of power systems in the 21st century. Both distribution and power generation are developing towards automation and distributed energy structure. However, in this process, the power system will be affected by a large number of non-linear factors, such as harmonics and voltage fluctuations. At the same time, it also makes the distribution system become a very complex network, which reduces the power quality [1]. The concept of big data and the development and application of technology gives a new breakthrough to China's power grid system. Therefore, the national smart grid strategy model based on large data analysis has been well applied [2, 3].

However, in the smart grid system, after a long-term and uninterrupted evaluation and monitoring of the key points of the power grid, it constitutes an effective large steady-state data of power quality. Through the corresponding data mining, the power quality indicators in a specific area are evaluated and predicted, and the corresponding trend changes of power quality at monitoring points can be obtained in advance [4]. Nowadays, there are a lot of problems in the operation of distribution and power generation systems. Through the correlation analysis of steady-state power quality indicators, this problem can be well solved. The influence of steady-state power quality problems is wide and deep. There are many relative factors affecting the change of power quality steady-state index in power system, such as voltage deviation and power flow separation, power supply distance and reactive power capacity, three-phase voltage unbalance and system planning, distribution structure, power network structure parameters and so on. If these factors are considered comprehensively, the corresponding difficulty and complexity of evaluation, prediction and monitoring will be greatly increased [5].

Based on this, a power quality steady-state index evaluation and prediction system model is designed in this study, which combines chaotic system theory and least squares support vector machine (LSSVM). Chaotic system theory is based on phase space reconstruction, which can extend a certain time series to a specific embedded space architecture, and find its potential evolution law in data information. LSSVM maps the data information of input space into high-dimensional space in a non-linear way, calculates and solves it in the corresponding high-dimensional region, and then input relative variables and output relative variables, so as to obtain the non-linear relationship between the input and output relative variables. The premise of the system design in this study is not to consider many other factors directly. The monitoring data information of power quality steady-state index evaluation and prediction is considered. Particle swarm optimization (PSO) is used to optimize LSSVM parameters, which reduces the complexity and difficulty of steady-state index evaluation and prediction. The superiority of the system model has been proved by the application of corresponding cases.

2. Methodology

2.1 Process design of evaluation and prediction system

For the evaluation, monitoring and prediction of the main indicators of power quality, the change trend of power quality at the corresponding monitoring points can be obtained in advance, which causes the corresponding operation of power grid and the attention of managers to potential power quality problems, so as to provide correct decision-making for the management and protection of power quality problems. At present, in China's power quality forecasting, monitoring and evaluation system, data collection and collation are carried out by day, week, month, season and year. Quantitative statistics is often used as index data with probability values approaching 96%. According to previous data statistics, it is found that the trend change of power quality steady-state index has the characteristics of quasi-periodic and non-periodic. In chaos theory, this trend can be restored by spatial reconstruction. For this reason, a prediction system model based on chaotic system theory and LSSVM is designed. The design process is shown in figure 1.

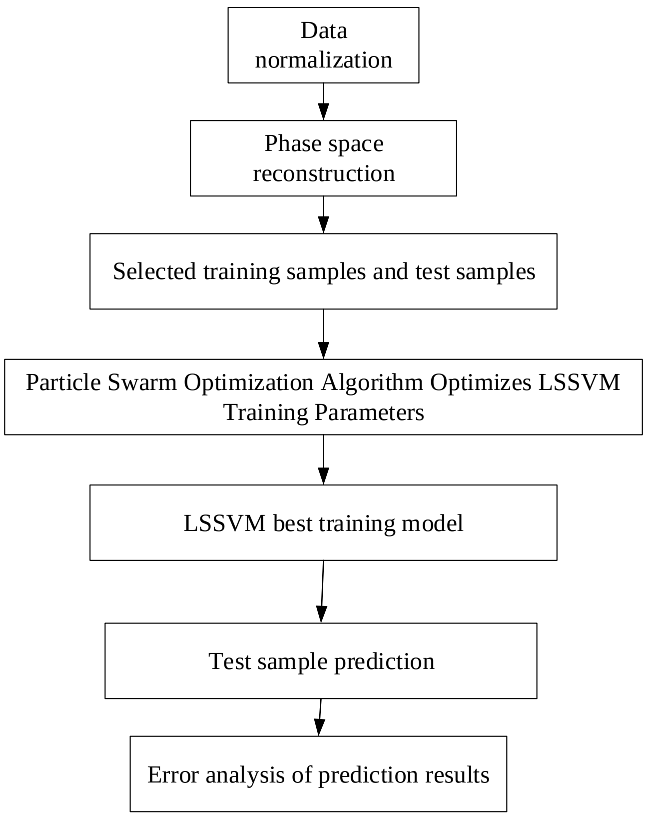

Figure. 1 Flowchart of forecasting model of power quality steady state indices

In the figure above, the process of power quality steady-state index evaluation and prediction system mainly includes the following steps.

Firstly, the data of power quality steady-state index evaluation and prediction system are pre-processed, and the abnormal data are judged, corrected, and normalized. According to Laida theorem [6], the abnormal data information is identified and the steady-state index sequence x = {xi/i=1, 2,...n} in power quality assessment is obtained. The corresponding mean value $\bar{x}$ and residual error vi are obtained.

$$v_i = x_i - \bar{x}(i = 1, 2, \cdots, n) \quad (1)$$

According to Bessel expression, the corresponding standard error σ is calculated. If the detection value xk(1≤k≤n) satisfies [7]:

$$|v_k| = |x_k - \bar{x}| > 3\sigma \quad (2)$$

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Then, xk is judged as an abnormal value, and the average value of the values in the two monitoring points at the adjacent time points is identified and corrected.
Secondly, the optimal mosaic frequency m and the optimal delay time point τ are obtained by the corresponding improved C-C method [8], and the phase space reconstruction of the steady state index of the electric energy treatment quantity is performed. At the same time, the largest Lyapunov exponent is calculated by the small data method [9], and the chaotic model of the sequence is entered.

Thirdly, according to the phase space trajectory expression theory in chaos theory [10], the training sample and the test sample are taken.

Fourthly, the LSSVM is used to test and train the newly extracted samples in the high-dimensional region, and the PSO algorithm is used to find the optimized normalized numerical parameters C and numerical parameters δ.

Fifthly, the trained LSSVM system [11] is used to evaluate the steady state index in the power quality assessment, and the corresponding error analysis operation is performed.

The main links of the steady state index evaluation and prediction system in the power quality assessment mentioned above is phase region reconstruction and LSSVM and parameter optimization, which will be elaborated on the following.

2.2 Phase space reconstruction of chaos theory
Chaos theory is finally reached into a specific trajectory through a series of evolutions. The reconstruction of phase space is an effective way to explore and analyze the dynamic behavior of chaotic theory system model. Reconstruct attractors with certain data information is used to analyze the corresponding chaotic characteristics of the system model. Among them, when the mosaic dimension m meets $m \geq 2d+1$ (d refers to the dynamic correlation dimension), the system model after the delay coordinate redistribution is equivalent to the corresponding prime mover system in the topological sense. At the same time, the chaotic sequence x={xi/i=1, 2, . . . , N} is considered. m represents the mosaic dimension, and τ represents the time delay. Then, the phase space is reconstructed, and the following formula [12] is obtained:

$$X = \left\{ X_i \,/\, X_i = [x_i, x_{i+\tau}, L, x_{i+(m-1)\tau}]^T, i = 1, 2, L, M \right\} \qquad (3)$$

In the formula, M=N-(m-1)t is the corresponding number of points in the phase space. In the process of phase space reconstruction, the values of mosaic dimension m and delay time point τ have a great influence on the accuracy of evaluating prediction monitoring. In this study, the improved C-C method is applied to perform corresponding phase space reconstruction.

After the phase region is redeployed, the steady-state indicator sequence in the power quality assessment becomes a corresponding multi-dimensional spatial data information set, but still maintains the same dynamic equivalence property as the original model system. Therefore, there is a certain smooth map f: Rm → Rm, which refers to the attractor of the trend of the sequence. The corresponding trajectory formula for phase space is [13]:

$$X(t+1) = f(X(t)), t = 1, 2, \cdots, M \qquad (4)$$

The above mapping can be expressed as [14]:

$$\begin{aligned}&(x(t+\tau), x(t+2\tau), L, x(t+m\tau)) = \\ &f(x(t), x(t+\tau), L, x(t+(m-1)\tau))\end{aligned} \qquad (5)$$

In formula 5, in the mathematical model of steady-state index sequence evaluation and prediction monitoring in power quality assessment, the computational solution of the mapping relationship f is the top priority of this model system.

2.3 The optimization of LSSVM
In order to better express the attractors of the steady-state indicator sequence in the power quality assessment, that is, the mapping relationship f mentioned above, the corresponding training samples (xtrain, ytrain) are selected. xtrain and ytrain generally do not have a corresponding linear relationship. Using the LSSVM can map xtrain into high-dimensional space [15], and the relationship between xtrain and ytrain can be transformed into a linear ambiguous estimation problem. If the regression function is:

$$y = w^T \varphi(x) + b \qquad (6)$$

In the formula, x refers to the training input xtrain obtained by re-sequencing the steady-state indicator sequence in the power quality assessment through the phase region; y refers to the ytrain of the rigorous training output; w refers to the normal vector; b refers to the offset. The solution to the relational operation of x and y can be expressed as:

$$\begin{aligned}&\min_{w,b,e} J(w,b,e) = \frac{1}{2}\|w\|^2 + \frac{C}{2}\sum_{i=1}^{k}\xi_i^2 \\ &s.t. y_i - \xi_i = w^T\varphi(x_i) + b, i = 1, 2, \cdots k\end{aligned} \qquad (7)$$

In the formula, C denotes the normalization parameter, and ξi denotes the relaxation variable; e= [1, ... 1] T. By introducing Lagrange function, formula 8 can be obtained [16]:

$$L(w,b,e,a) = J(w,b,e) + \sum_{i=1}^{k} \alpha_i [y_i - \xi_i - w^T \varphi(x_i) - b] \quad (8)$$

In the formula, ai represents the multiplier of Lagrange function [17]. From the Karush-Kuhn-Tucker (KKT) [18] condition, it can be concluded that:

$$\begin{aligned} \frac{\partial L}{\partial w} &= 0 \rightarrow w = \sum_{i=1}^{k} \alpha_i \varphi(x_i) \\ \frac{\partial L}{\partial w} &= 0 \rightarrow y_i - \xi_i - w^T \varphi(x_i) - b = 0 \\ \frac{\partial L}{\partial w} &= 0 \rightarrow \sum_{i=1}^{k} \alpha_i = 0 \\ \frac{\partial L}{\partial w} &= 0 \rightarrow \alpha_i = C\xi_i \end{aligned}$$

(9)

The solution of the above formula can be transformed into:

$$\begin{bmatrix} 0 & e^T \\ e & Q + C^{-1} I \end{bmatrix} \times \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix}$$

(10)

In the formula, I denotes the identity matrix; a= [a1,... ak]T; y=[y1, ... yk]T; Q refers to k * k order kernel matrix of Kij, where Kij = ((φ(xi), (φ(xj)). If Qn = Q + I / C, the formula 11 is obtained:

$$\begin{cases} b = \dfrac{e^T Q_n^{-1} y}{e^T Q_n^{-1} e} \\ \alpha = Q_n^{-1}(y - e \times b) \end{cases} \quad (11)$$

The radial basis function is used as the kernel function.

$$K(x_i, x_p) = \exp(-\|x_i - x_p\|^2 / 2\delta^2) \quad (12)$$

In the formula, δ2 is the corresponding variance of the kernel function. From formula 10 to 12, the formula of steady-state index evaluation and prediction system in power quality assessment is as follows:

$$y = f(x) = \sum_{i=1}^{k} \alpha_i K(x_i, x) + b \quad (13)$$

The prediction input XP is substituted into the above formula to obtain the prediction value

$$y_p = f(x_p) = \sum_{i=1}^{k} \alpha_i K(x_i, x_p) + b$$

(14)

2.4 LSSVM parameter optimization based on PSO

In the process of training and monitoring the LSSVM, the values of normalized numerical parameter C and numerical kernel parameter δ are particularly important. In order to optimize the evaluation and prediction system, the PSO algorithm is used to find the optimal numerical parameter C and the numerical kernel parameter δ [19].

In PSO, random particles update the corresponding velocity and position relationship by searching individual extreme value Pbest and group extreme value gbest. In this way, after repeated updates, the global optimal solution of the group is finally found. The updating formula of particle velocity and position information is as follows:

$$v_{t+1} = wv_t + c_1 r_1 (p_{best} - x_t) + c_2 r_2 (g_{best} - x_t) \quad (15)$$

$$x_{t+1} = x_t + v_{t+1} \quad (16)$$

In the formula, vt and xt respectively refer to the speed and coordinates of the particle's t-th update; w refers to inertial weights; r1 and r2 refer to random values in the region [0, 1]; c1 and c2 refer to learning factors [20].

The detailed steps of optimizing the corresponding numerical parameters by using PSO algorithm [21] are as follows:

Firstly, the numerical parameters are initialized. The information of particle size, update times, learning factors and particle accident location and speed are set.

Secondly, the normalized numerical parameter C and the numerical kernel parameter δ are considered as a set of random particles. Each group of particles corresponds to a LSSVM model. In the current model, xtrain and ytrain are trained. The predicted and actual values are compared and the particle adaptation values in this coordinate are obtained.

Thirdly, in the relative motion of particles, the adaptive values in different coordinates will be obtained. Each movement of the particle is then compared in size. The relatively small adaptive values are corresponded to the corresponding coordinate positions and are taken as the current optimal coordinate positions of the particle.

Fourthly, by comparing the fitness values between the particles in the same time period, the fitness values with smaller values are corresponded to the position of a particle, and then are taken as the current optimal coordinate position information in the population. At the same time, the particles are updated by formula 15 and formula 16.

Fifthly, whether the maximum number of updates has been reached is checked. If it meets the corresponding conditions, it is necessary to finish the calculation and output the corresponding numerical results, or return to the second step for recalculation.

2.5 Case study and contrast test

Through the design of the voltage quality steady-state index evaluation and prediction system mentioned above, using chaos theory, and combining the optimized LSSVM algorithm and improved PSO algorithm, a smart grid voltage quality steady-state index evaluation system based on large data analysis is obtained. In order to further prove that the system can be better applied, the voltage quality steady-state index evaluation and prediction system designed in this study is applied to a substation monitoring point for test experiments. At the same time, it is compared with BP neural network method [22] to verify its optimization degree.

In order to quantify the accuracy of analysis and prediction, relative error Ere, average relative error Emre and root mean square error Ermse are introduced to obtain the following formula [23]:

$$E_{re} = \frac{F(i) - L(i)}{L(i)} \cdot 100\% \qquad (17)$$

$$E_{mre} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{F(i) - L(i)}{L(i)}\right| \cdot 100\% \qquad (18)$$

$$E_{rmse} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(F(i) - L(i))^2} \qquad (19)$$

In the formula, F(i) refers to the predicted value and L(i) refers to the actual value. The three formulas are used to further verify whether the BP neural network method and the optimization system involved in this study have smaller and more accurate relative error maximum, average relative error and root mean square error.

3. Results and discussion

3.1 Experimental analysis of a case

In the steady-state index of power quality evaluation, the data information monitored on the day is taken as the daily index value, and the large data collected by the power quality evaluation and prediction monitoring system of a certain power grid is taken as the experimental sample. The index values of voltage deviation, distortion rate of total harmonics, unbalance of three-phase voltage and long-term flicker are evaluated and predicted. Taking the deviation value of voltage as a sample, the evaluation and prediction process of power quality index is described concretely.

Figure 2 reflects the time series of voltage deviation daily indicators of a 10kV substation monitoring point in 2016-2018. Considering that the network structure, load classification and volume capacity of the predictive monitoring point have not changed much in a certain period of time, the detected data can be taken as corresponding experimental samples.

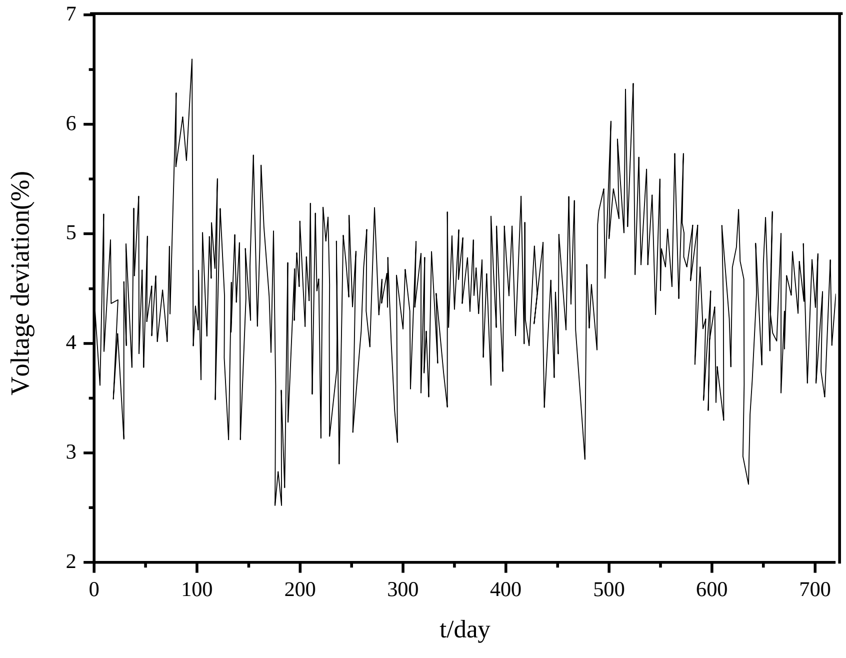

Figure. 2 Raw voltage deviation time series

By using the improved C-C method mentioned above, the phase-area redistribution parameters of the sequence of voltage deviation time points are calculated, and the first partial minimum of $\Delta \bar{s}_1(t)$ is taken as the optimal delay τd.

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The periodic point of $\left| \bar{s}_1(t) - \bar{s}_2(t) \right|$ is regarded as the optimal embedded window τ w. Through the formula τw=(md-1) τd, the optimal embedding dimension md can be obtained. The corresponding results are shown in figure 3, and τd=12.1, τw=96.2, and md=9.02 are obtained.

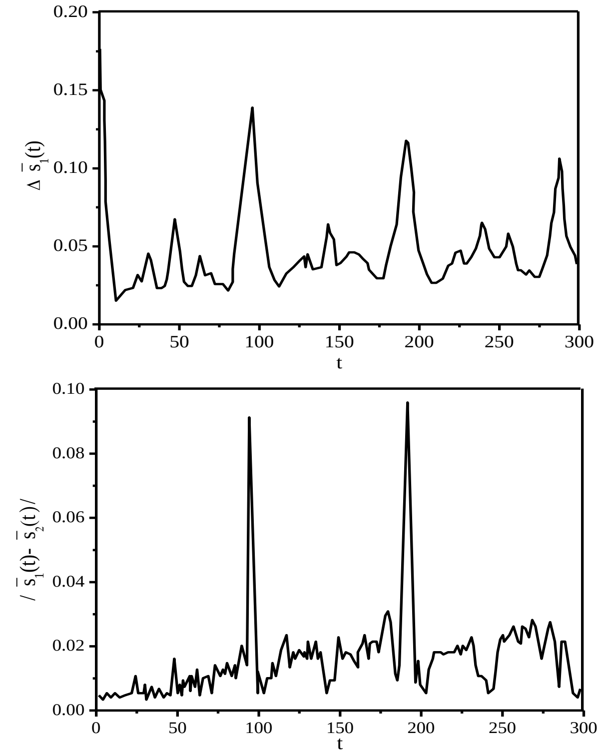

Figure. 3 Reconstruction parameters based on improved C-C method

According to the obtained td and md, the maximum Lyapunov exponent of the time series of voltage deviation is calculated by using the small data information method. If the end shows a positive number, the time series has certain chaotic characteristics. Figure 4 shows the Lyapunov exponential curve of the time series of voltage deviations. k represents the steps of discrete time evolution, and y (k) represents the logarithmic average of distance. It can be seen that within the K interval [0, 200], y (k) is approximately a straight line, and its slope is the highest Lyapunov index λ. It can be calculated λ = 0.043, which indicates that the sequence of voltage deviation time points at this point has chaotic characteristics.

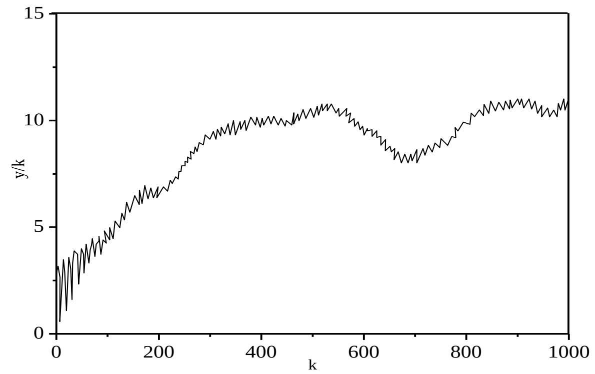

Figure. 4 Lyapunov exponent curve of the voltage deviation time series

md = 9.02, and td = 12.1 are substituted into formula 3. For the reconstruction of phase region of voltage deviation time series, training samples (xtrain, ytrain) are adopted. LSSVM is used to train its parameters in high dimensional space. According to PSO, the LSSVM model is optimized to obtain population number N = 30, learning factor c1 = c2 = 1.45, maximum update number Tmax = 502, and inertia weight W = 0.92. Search range C∈[0, 502] and δ∈[0, 50] are set. At the same time, the LSSVM toolbox is used to make some simulation comparisons with a certain web search method.

3.2 Comparisons with web search method

In figure 5, PSO and web search are used to optimize the parameters of LSSVM model, and the fitness is the root mean square error of the predicted and actual values in the corresponding training samples.

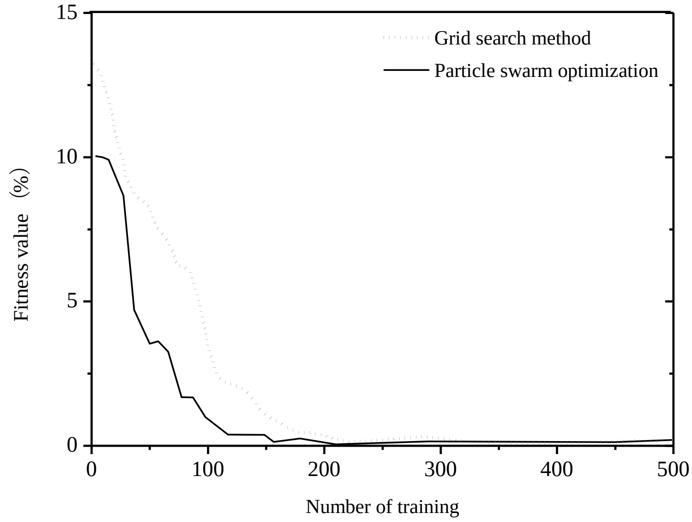

Figure. 5 Fitness curves based on PSO and grid search method

Thus, compared with the grid search method, PSO has faster convergence speed on the adaptive curve, and the corresponding values are obtained: C = 73.127, δ = 0.742.

3.3 Comparison with BP neural network

The C=73.127 and the δ=0.742 obtained above are substituted into the LSSVM model. According to the corresponding chaotic theory, the reciprocal value of Lyapunov exponent λ, Tm=1/λ refers to the upper limit of predictive monitoring time in the chaotic theory system, that is, the longest predictive time. The maximum Lyapunov exponent λ = 0.043 for the sequence of voltage deviation time points, thus Tm = 21.23d is obtained. At the same time, on the basis of guaranteeing the prediction accuracy, the daily voltage deviation of the monitoring point in December 2018 is evaluated and predicted. In the process of forecasting, the forecasting value of each step is retained, and then it is used as the reference value for the next step.

In order to explore the rationality and practicability of the proposed evaluation and prediction system model, the system and BP neural network method are compared and tested. The results are shown in figure 6.

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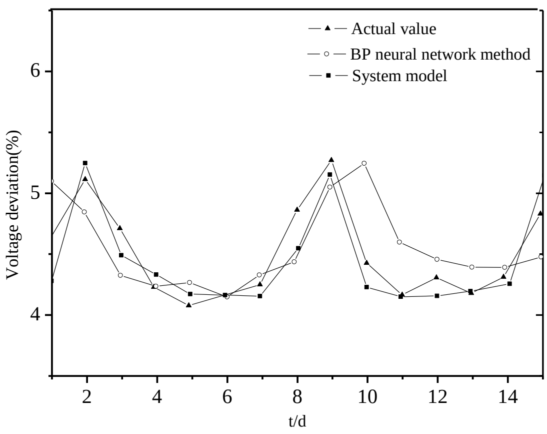

Figure. 6 Forecasting results of voltage deviation

From the figure, it can be seen that the predicted results based on chaotic theory system and LSSVM are similar and closer to the actual values. It can be known that the evaluation system designed in this study is an evaluation and prediction system based on BP neural network method. Secondly, in order to further test the accuracy of the system, the maximum relative error, average relative error and mean square error of the system prediction are compared with the BP neural network method. The specific comparison results are shown in table 1. The average relative error is less than 7%.

Table. 1 Forecasting results of voltage deviation

Time	Actual value/%	BP neural network method		This paper designs the system model	
		Predictive value/%	E_{re}/%	Predictive value/%	E_{re}/%
12-01	4.612	5.121	10.431	4.321	-6.872
12-02	5.087	4.832	-5.021	5.197	3.176
12-03	4.656	4.312	-8.132	4.490	-3.765
12-04	4.233	4.197	-0.637	4.401	1.568
12-05	4.087	4,265	3.781	4.166	1.436
12-06	4.176	4.323	0.541	4.137	-0.745
12-07	4.301	4.398	1.276	4.097	-2.043
12-08	4.825	5,109	-8.605	4.478	-6.436
12-09	5.266	5.231	-3.834	5.204	-2.143
12-10	4.377	4.456	19.12	4.231	-4.452
12-11	4.126	4.564	9.23	4.126	0
12-12	4.254	4.387	3.677	4.178	-2.798
12-13	4.209	4.367	5.124	4.561	0.439
12-14	4.298	4.278	1.198	4.143	-1.107
12-15	4.785	4.432	-7.561	5.234	6.231
E_{mre}	-	5.912%		2.834%	
E_{rmse}	-	0.324%		0.163%	

From table 1, the steady-state index evaluation system designed in this study has advantages in the approximation of relative error, average relative error and root mean square, and this system is more accurate.

3.4 Discussion

The steady state index in power quality assessment reflects the state of power system under stable operation. After the design of the steady-state index evaluation and prediction system in power quality assessment, the chaos theory and LSSVM and PSO algorithm are used to construct the system. C-C method and small data quantization are used to enter the sequence operation. Through the corresponding empirical application analysis, compared with the actual error prediction value of network search method and BP neural network method, it is concluded that the steady-state index evaluation system in power quality evaluation in this study has great advantages.

4. Conclusion

Based on the background of large data, the steady-state index evaluation system for power quality evaluation of smart grid is designed and applied. Chaos theory system, LSSVM and PSO are used to construct the system. It is concluded that the system designed in this study has faster convergence speed and training accuracy than the web search method. At the same time, it is concluded that voltage deviation, total harmonic distortion rate, three-phase voltage unbalance and long-term flicker have chaotic characteristics among the factors affecting the change of steady-state index in power quality assessment. In addition, the improved C-C method is introduced. By calculating the optimal mosaic dimension and the optimal system delay with local or partial minima and periodic correspondence points, the relevant characteristics of chaotic attractors can be well mapped. At the same time, by comparing the designed system algorithm with BP neural network algorithm, it is concluded that the prediction results of local chaotic system and LSSVM model are more accurate and closer to the actual values than those of BP neural network. In addition, it is superior to BP neural network in terms of maximum relative error, root mean square error and average relative error. The average relative error of steady-state index evaluation and prediction in power quality evaluation is less than 7%. The design of this system will bring new technology reference for the application of smart grid system based on large data background. At the same time, more and more attention has been paid to the research of early warning system of steady-state indicators in power quality assessment. It is hoped that experts, and scholars will make joint efforts to reduce voltage and improve the quality of power supply.

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