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Simulation Study on Optimizing Neural Network in Short-Term Electric Load Prediction

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Abstract

It researches the short-term electric load prediction and short-term electric load has the characteristics of time-varying, uncertainty, nonlinearity, etc., so the traditional linear prediction method cannot correctly describe the changing rule of the short-term electric load prediction, and neural network has the deficiencies including local minimum value of neural network, over-fitting and weak generalization ability, and the prediction accuracy is lower. In order to improve the accuracy of the short-term electric load prediction, this paper proposes a short-term electric load prediction model (IQPSO-BPNN) based on optimizing BP neural network. Firstly, it improves Quantum Particle Swarm Optimization to optimize the BP neural network parameters, and then adopts the optimized BP neural network to conduct modeling for the nonlinear change law of the short-term electric load prediction. Finally, it takes simulation test for the model performance. The simulation result shows that IPQPSO solves the problems of the BP neural network, and improve the prediction accuracy of the short-term electric load and reduce the prediction error.

***Keywords**: Electric load; Prediction accuracy; Quantum particle swarm optimization; Neural network; Variable element*

1. Introduction

Short-term electric load prediction refers to predicting the load condition in the coming days, a few hours or even shorter time, and is the basis for electric power system department to arrange the unit start-stop and make the power purchase plan. Load is affected by factors such as weather, holidays, *etc.* and the law is difficult to grasp, so the short-term electric load prediction has always been the hot spot of the domestic and foreign research [1].

For a long time, people have done lots of researches on short-term electric load prediction and proposed many effective prediction methods. The main short-term electric load prediction method is divided into two categories: mathematical statistics prediction method and artificial intelligence f prediction method [2]. Mathematical statistics method mainly includes regression analysis, time series method, *etc.* [3-4]. These methods are simple and easy to implement. But the short-term load is the complex nonlinear system affected by many factors, these methods are difficult to accurately describe the short-term load's changing characteristics of periodicity and non-stationary, and there is certain gap between prediction accuracy and actual requirement. Artificial intelligence prediction method is a kind of heuristic method, including artificial neural network, support vector machine, *etc.* In some scenarios, it can overcome the defects of traditional methods [5]. Among them, the BP neural network does not need prior knowledge and can take infinite approximation to nonlinear system, becoming the most widely used short-term electric load prediction algorithm [6]. But the BP neural network prediction performance is

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closely related to parameters such as initial connection weights and threshold value, *etc.*, therefore, to take advantage of the BP neural network to improve the short-term electric load prediction, it must find the optimal network parameters. Currently, the BP neural network parameter optimization method mainly includes: genetic algorithm (GA) and particle swarm optimization (PSO) algorithm, ant colony optimization (ACO) algorithm, simulated annealing (SA) algorithm, *etc.* [7]. These algorithms have shortcomings, and are difficult to find the optimal initial connection weights and threshold value, causing the prediction result of BP neural network is not stable, and sometimes it difficult to make people satisfactory [8]. In 2004, Jun Sun *et al*. put forward a new optimization algorithm - Quantum Particle Swarm Optimization (QPSO), which has the advantages of a few operating parameters, easy programming, easy implementation and high applicability, so it is widely followed [9].

In order to improve the prediction accuracy of short-term load, this paper puts forward a model of short-term load prediction (VPQPSO-BPNN) based on the optimized BP neural network. Firstly, by phase-space reconstruction, it conducts reconstitution for the historical data of short-term load, and then through VPQPSO algorithm, it finds the optimal parameters of BP neural network, and finally establishes the optimal short-term load prediction model, and test the model performance by simulation experiment.

2. The Prediction Principle of Short-Term Load

The change of the short-term load is influenced by multiple factors, assuming that these influencing factors are expressed as: $Y = \{X_1, X_2, \cdots, X_n\}$. Y represents the real value of short-term load, *X*i represents the ith influencing factors; through the adoption of certain modeling method to reflect the nonlinear relationship between short-term load and the influencing factors, the mathematical expression of prediction model is as follows:

$$Y' = f(X_1, X_2, \cdots, X_n) \tag{1}$$

From the formula (1), the principle of short-term load prediction is to establish prediction model *f*() based on the historical data of the short-term load collected and its influencing factors, to make the real value of the short-term load *Y* and predictive value Y' with the minimum error, thus it takes short-term load prediction at some point in the future [10].

Short-term load change is characterized by real degeneration, uncertainty and nonlinear *etc.* The traditional linear prediction method cannot correctly reflect the short-term load change law, and the neural network has strong nonlinear predictive power, but if the parameters are not selected properly, with local minimum value, over-fitting and weak generalization ability, *etc.* Quantum Particle Swarm Optimization algorithm has the advantages of a few Quantum Particle Swarm Optimization operating parameters, easy programming, easy implementation and high applicability, *etc.*, and it is very suitable for neural network parameter optimization selection, thus, this paper uses the BP neural network with strong nonlinear prediction ability to forecast the short-term load, and use the VPQPSO algorithm to optimize the BP neural network parameters, and then eventually improve the short-term load prediction accuracy. The structure chart of prediction principle is shown in Figure 1

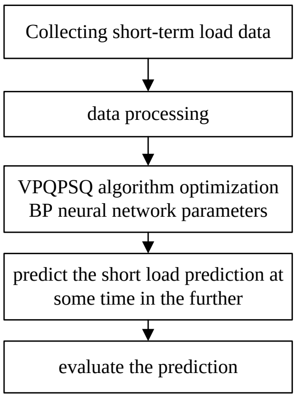


Figure 1. Structure Chart of Prediction Principle

3. VPQPSO-BP Neural Network Short-Term Load Prediction Model

3.1. BP Neural Network

Assume the short-term load time series input is $X(t) = (x(t), x(t+\tau), \mathbf{n}, x(t+(m-1)\tau))^T$, and the corresponding output is $y(t)$, the BP neural network's node point number of input layer is short-term load embedding dimension m, output is short-term load expected, the BP neural network completes the mapping $f: R^m \to R^1$, and the input of the hidden layer node is as follows

$$S_j = \sum_{i=1}^{m} w_{ij} x_i - \theta_j \tag{2}$$

Wherein, wij is the initial connection weighting from input layer to hidden layer; θj is the initial connection weighting of hidden layer.

Sigmoid function is used as the transfer function of BP neural network, namely

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

The output of nodes in hidden layer of the BP neural network is as follows:

$$b_j = 1 / \left(1 + \exp\left(\sum_{i=1}^{m} w_{ij} x_i - \theta_j \right) \right), j = 1, 2, \mathbf{n}, p \tag{4}$$

Similarly, the output and input of nodes of input layer are respectively

$$\mathrm{V} \begin{cases} L = \sum_{j=1}^{p} w_{jk} b_j - \theta_k \\ x_{i+1} = \dfrac{1}{\left(1 + \exp\left(\sum_{j=1}^{p} v_j b_j - \gamma \right) \right)} \end{cases} \tag{5}$$

Wherein, *vj* is the connection weight between the hidden layer and output layer; *γ* is the threshold value of the output layer.

Before the BP neural network training, it is necessary to select the most appropriate initial connection weights and thresholds. Generally, the random fashion is used for initialization, which is easy to make the BP neural network with some deficiencies including the slow convergence speed, and being easy to fall into local optimal solution, *etc*. influencing the BP neural network learning and generalization ability, therefore, based on Quantum Particle Swarm Optimization (QPSO) to optimize the BP neural network parameters.

3.2. VPQPSO Algorithm

In particle swarm algorithm (PSO), the particle represents the potential solution of optimization problem, and the particles in the solution space follow other particles to search in the solution space, to find the optimal solution through continuous iteration. Set $Xi=[xi,1,xi,2,\ldots,xid]$ and $Vi=[vi1,vi2,\ldots,vid]$ as the current position and velocity of particle i, respectively, $Pi=[pi1,pi2,\ldots,pid]$and $pg=[pg1,pg2,\ldots,pgd]$ are respectively particles i and the best location that the has group experienced, the updating formula of particle velocity and position is

$$v_{ij}(t+1)=\omega v_{ij}(t)+c_1\times r_1\times\left(p_{ij}-v_{ij}(t)\right)$$
$$c_2\times r_2\times\left(p_{gj}-v_{ij}(t)\right) \tag{6}$$

$$x_{ij}(t+1)=x_{ij}(t)+v_{ij}(t+1) \tag{7}$$

Wherein, $c1$, $c2$ is acceleration coefficient; k is the current iterations; $r1$ and $r2$ are the random numbers within the scope of [0, 1]; ω is inertia weight [11].

Although PSO algorithm has the advantages of a fewer control parameters, easy implementation, it can't converge to overall optimal solution with the probability of 100%, therefore, Jun Sun *et al*. started from the perspective of quantum mechanics to propose a new PSO algorithm - Quantum Particle Swarm Optimization (QPSO), to ensure that the algorithm is convergent to the overall optimal solution. The best location point on average of all the particles in the quantum particle swarm is mbest (Mean Best Position), mbest is defined as:

$$\begin{aligned} mbest(t) &= \frac{1}{M}\sum_{i=1}^{M} p_i(t) \\ &= \left[\frac{1}{M}\sum_{i=1}^{M} p_{i1}(t), \frac{1}{M}\sum_{i=1}^{M} p_{i2}(t), \ldots, \frac{1}{M}\sum_{i=1}^{M} p_{id}(t),\right] \end{aligned} \tag{8}$$

In the QPSO algorithm, each particle must converge to their respective random point P, the dth dimension of the ith particle position is:

$$x_{id}(t+1)=p_{id}\pm\frac{L_{id}(t)}{2}\ln[1/u_{id}(t)] \tag{9}$$

Wherein, u_{id} is random numbers uniformly distributed on the (0, 1); the value of $L_{id}(t)$ is determined by:

$$L_{id}(t)=2\alpha(t)\left|mbest_{id}(t)-x_{id}(t)\right| \tag{10}$$

So, the updating formula for the particle position of QPSO algorithm is:

$$\begin{aligned} x_{id}(t+1) = {} & p_{id}(t)\pm\alpha(t)\times\left|mbest_{id}(t)-X_{id}(t)\right| \\ & \times\ln(1/u_{id}(t)) \end{aligned} \tag{11}$$

Wherein, α is called the contraction- expansion coefficient.

The updating formula of current optimal location of particle Pi and the overall optimal location Pg is:

$$P_i(t+1)=\begin{cases} x_i(t+1) & if\ \ (x_i(t+1))< f(p_i(t+1)) \\ p_i(t) & if\ \ (x_i(t+1))\geq f(p_i(t+1)) \end{cases} \tag{12}$$

Wherein, f() is the objective function.

In QPSO algorithm, in addition to the group size, dimensionless number and iterations, the only control parameter is the contraction- expansion coefficient in (11) formula, α , and its role in the algorithm is able to adjust the convergence process of the algorithm. With simulation results, the literature [12] concludes when $\alpha \leq 1.7$, the particle swarm converges; $\alpha \geq 1.8$, the particle swarm diverges. The easiest way to control parameter α is to fix the value of α , but it will reduce the algorithm performance. The current good method is to take the linear transformation for α , as shown in formula (13), but the performance improvement is limited.

$$\alpha(t) = m - (m - n) * t / \max times \tag{13}$$

wherein, m, n are the constant. *MaxTimes* is the maximum iterations.

In order to make the QPSO algorithm with better adaptability, this paper proposes a variable parameter quantum particle swarm optimization algorithm (VPQPSO). Parameter α of VPQPSO algorithm is defined as:

$$\alpha(z) = \begin{cases} 0.4 & z > 0 \\ 0.6 - 0.1 \times k & -2 < z \le 0 (k = 0,1,2) \\ 0.6 + 0.1 \times k & -k - 1 < z \le -k (k = 3,4,5) \\ 1.0 + 0.2 \times (k - 4) & -k - 1 < z \le -k (k = 6,7,8) \\ 1.7 & z \le -9 \end{cases} \tag{14}$$

Wherein, $z = \log(\Delta F)$, ΔF is the error function, the definition is as follows.

$$\Delta F = \frac{f(p_i) - f(p_g)}{Min(f(p_i), f(p_g))} \tag{15}$$

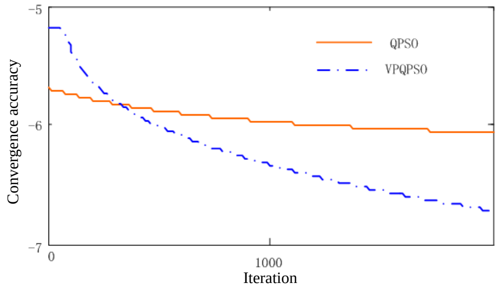
Wherein, *f*(*pi*) is the fitness value of *Pi*, *f*(*pg*) is the fitness value of *pg*, *Min*( ) is the minimal function.

To test the performance of VPQPSO algorithm, six commonly used benchmark functions (the minimum value of solution) are chosen to compare the performance of VPQPSO algorithm and QPSO algorithm, the function form, search range, theoretical extreme value and convergence accuracy are shown in Table 1. Figure 2 is the carves of 6 test function fitness for numerical evolution (note: in order to facilitate the display and observation of the evolution curve, in this paper, the function of the fitness value is the logarithm of 10), The full line in the Figure is convergence curve line of QPSO, and the imaginary line is the convergence curve of VPQPSO.

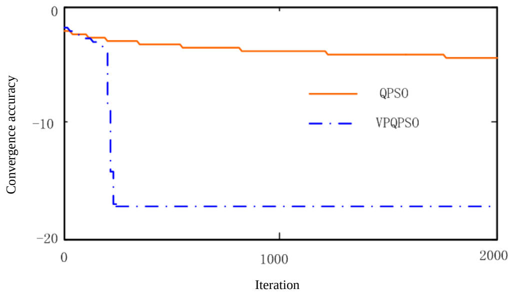
From Figure 2, it can be concluded that for all functions, the convergence rate of VPQPSO is obviously better than that of QPSO. For Rastrigin with multiple peak values and Schaffer with highly oscillatory and multiple peak values, VPQPSO can quickly achieve the theoretical minimum point 0 and -1, and avoid making the QPSO with the shortcoming of local optimum, which shows that the changing value of parameter a by adaptive value can make VPQPSO's overall search ability, convergence accuracy and convergence rate better than the traditional QPSO algorithm.

Table 1. Function of Testing Algorithm Performance

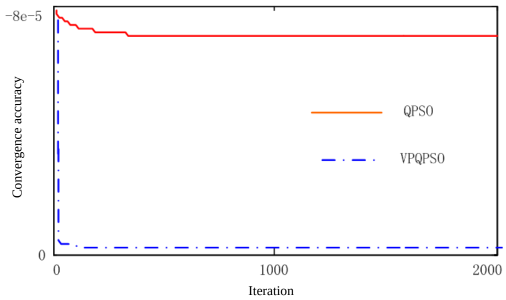
Name of function	Function form	search range	theoretical extreme value	convergence precision
Griewank function	$f(x) = 1/4000\sum_{i=1}^{n}(x_i)^2 - \prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}}) + 1$	[-600,600]	0	10-6
Rastrigin function	$f(x) = \sum_{i=1}^{n}(x_i^2 - 10\cos(2\pi x_i) + 10)$	[-100,100]	0	0
Rastrigin function	$f(x) = \frac{\sin^2\sqrt{x_1^2 + x_2^2} - 0.5}{(1 + 0.001(x_1^2 + x_2^2))^2} - 0.5$	[-100,100]	-1	-1



(a) Convergence Curve of Griewank Function Fitness



(b) Convergence Curve of Rastrigin Function Fitness



(c) Convergence Curve of Schaffer Function Fitness

Figure 2. Comparison of Convergence Performance Between QPSO and VPQPSO

3.3. Working Step of VPQPSO-BPNN Load Prediction Model

Step1: collecting historical data of short-term load, and taking the pretreatment for it, making it divided into two parts, training sample and test sample.

Step2: randomly generating an set of initial quantum particles, making the initial connection weights and threshold of the BP neural network expressed as the individual particles in the population, and then according to the training sample, BP neural network takes study, according to the formula (16), calculating fitness function value of each quantum particle, and according to the fitness value, determining *Pi* and population extremum *Pg*.

$$f(t) = \sum_{t=1}^{n} (y_t - y_t)^2 \tag{16}$$

Wherein, y_t is the actual load, y_t is the output value of BP neural network, n is the sample quantity.

Step3: for each quantum particle, if its fitness value is superior to its own historical optimal location *Pi*, then the particle's location replaces *Pi*.

Step4: for each quantum particles, if its fitness value is superior to the group's optimal location *Pi*, then the particle's location replaces *Pi*.

Step5: making use of formula (8) to calculate *mbest*.

Step6: according to formula (10), (11), (14), (15), updating the particle's location.

Step7: If the maximum iteration is achieved, the overall optimal particle mapping is the initial connection weights and threshold of BP network, turning to Step8; otherwise, calculating fitness values of a new generation of particle swarm particle, and turning to step 3.

Step8: According to the initial connection weights and threshold, establishing BP neural network short-term load prediction model, and inputting short-term load test samples, testing the performance of short-term load prediction model.

4. Simulation Experiment

4.1. Data Sources

Data come from short-term load data per hour of Chengdu in Sichuan province on March 1, 2013 to March 30, 2013, and 720 short-term load data are collected, as shown in Figure 3. The first 600 data are the training set, and the remained 120 data are the test set. Experimental environment is: Pentium E5300 2.8 GHZ, 2GRAM, MATLAB 2009, and operating system is Windows XP SP3.

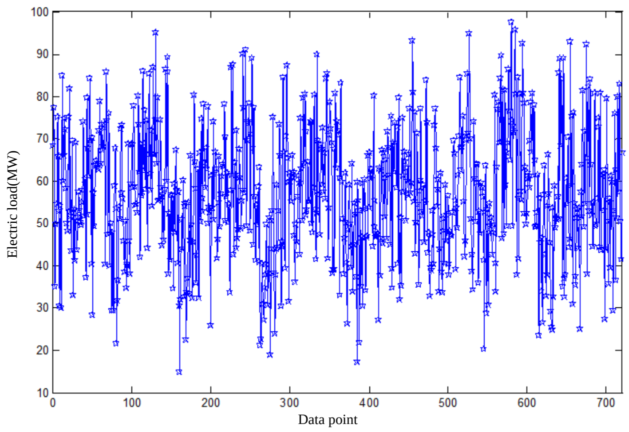


Figure 3. Original Short-Term Load Data

4.2. Comparison of Models and Evaluation Standards

In order to make the predicted results of VPQPSO - BPNN comparable, Quantum Particle Swarm Optimization to optimize the BP neural network (QPSO - BPNN) and literature [13] Quantum Particle Swarm Optimization to optimize the BP neural network (IQPSO - BPNN) are as comparison models. Evaluation standards are the average relative error (MAPE) and root-mean-square error (RMSE), their concrete definitions are:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_i}{y_i}\right| \times 100\% \qquad (17)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - y_i}{y_i}\right)^2} \qquad (18)$$

Wherein, y_i and y_i are respectively the real value and the predicted value of the short-term load, n is test sample.

4.3. Data Pretreatment

Firstly, mutual information is used to calculate τ =1, the method of CAO is used to choose m=7, then τ =1, m=7 is used; according to the formula (1), phase-space reconstruction is taken for short-term electric load data in Figure 2, to get a multidimensional short-term electric load data. Before modeling, pretreatment is conducted for the original short-term load data, to make them with the same scale, as follows:

$$\begin{cases} X(n,i) = \dfrac{X(n,i) - M\_X(n)}{D\_X(n)} \\ Y(n) = \dfrac{Y(k) - M\_Y(n)}{D\_Y} \end{cases} \tag{19}$$

Wherein, $M\_X(n)$, $D\_X(n)$, respectively, are mean and variance of the nth column of the input vector X; , $M\_Y(n)$, $D\_Y(n)$, respectively, are the mean and variance of the output vector Y.

4.4. Results and Analysis

The last 50 samples are test sample, and the rest is the training sample. Fitting results and predicted results of VPQPSO-BPNN, IQPSO-BPNN and QPSO-BPNN are shown respectively in Figure 4 and 5, the error of their fitting results and predicted results are shown in Table 2.

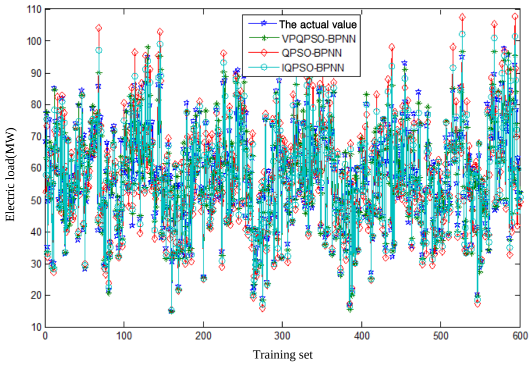


Figure 4. Comparison of Fitting Results of Several Electric Load Prediction Models

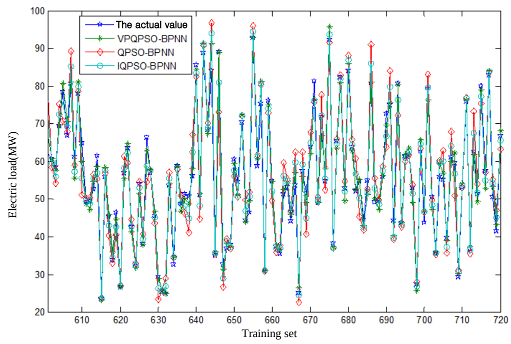


Figure 5. Comparison of Generalization Ability of Several Electric Load Prediction Models

Table 2. The Short-Term Power Load Forecasting Performance Comparison of the Model

Evaluation index	QPSO-BPNN	IQPSO-BPNN	VPQPSO-BPNN
RMSE	4.40	2.49	2.01
MAPE	6.14%	3.87%	3.39%
RMSE	5.59	3.57	2.51
MAPE	7.56%	4.81%	3.47%

In Figure 4, Figure 5, and Table 2, two kinds of models analyze fitting and prediction results of short-term load, and the following conclusion can be gained:

(1)The fitting value of VPQPSO – BPNN for the training sample perfectly fits the actual short-term load, the fitting precision is quite high, the fitting error is smaller than QPSO-BPNN, and slightly better than IQPSO-BPNN, which suggests VPQPSO algorithm can better overcome the defects of QPSO algorithm, and than get more optimal parameters of BP neural network than the quantum particle swarm optimization algorithm in literature [13], improving the fitting precision of short-term load prediction model.

(2) Prediction result of VPQPSO – BPNN for the test sample set is superior to those of IQPSO-BPNN model, QPSO-BPNN, which shows that the short-term load prediction model by using VPQPSO-BPNN is more comprehensive, and accurately depicts the short-term power load's time-varying and cyclical characteristics, generalization ability is better, thus improving the accuracy of short-term electric load prediction.

5. Conclusion

In the process of short-term electric load modeling, the BP neural network parameter has a great influence on the prediction results; in order to reduce the blindness of BP neural network parameter settings, it put forward the short-term electric load prediction model based on quantum particle swarm optimization algorithm to optimize BP network parameters. The simulation results indicate that the VPQPSO algorithm can effectively overcome the defects of QPSO algorithm, greatly improve the network training speed and generalization ability, and relative to other prediction models, VPQPSO - BP neural network can better describe the complex changes of the short-term electric load, to get better prediction effect with good engineering application value and practical significance.

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