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Short-term Power Prediction of the Photovoltaic System Based on QPSO-SVM

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Abstract

Short-term power prediction of the photovoltaic system is one of the effective means to reduce the adverse effects of photovoltaic power on the grid. Since the efficiency of the traditional support vector machine (SVM) prediction method is low, this paper proposes the SVM based on the parameter optimization method of quantum particle swarm optimization (QPSO), and then apply into the power short-term prediction of the photovoltaic system. After comparing and analyzing the prediction results of SVM based on three optimization methods, we find that the QPSO-SVM method has better precision and stability, which provides reference to forecast generation power of the photovoltaic system.

Keywords: *photovoltaic system, power prediction, SVM, QPSO*

1. Introduction

Development of science and technology leads to an enormous amount of energy consumption, the demand for energy is increasing rapidly. But the traditional fossil energy sources are not renewable. To find a new sustainable development way of the energy source is important in the future. Solar energy can meet human needs, photovoltaic power generation is one of the main uses of solar energy. In recent years, photovoltaic power generation is developing very rapidly, but photovoltaic power varies as the weather changes, it is uncertain and cyclical, large-scale photovoltaic power will make great impact on the photovoltaic grid-connected system. An accurate prediction of the photovoltaic can effectively alleviate this problem. How to accurately predict the output of photovoltaic power generation system attaches great importance to mastering the running characteristics of photovoltaic power generation system, and also to weakening the negative influence of photovoltaic power generation system for power grid, it has become a more and more important subject of the research on photovoltaic power.

It's difficult to predict the power of photovoltaic system because there are so many factors that affect the power of photovoltaic system. Now many methods are widely used in the photovoltaic power prediction such as time series prediction, artificial neural network, grey forecast, support vector machine (SVM) and so on [1-6]. SVM algorithm replaces experience minimization principle of the traditional machine learning theory by structural risk minimization principle. Compare to other algorithms, SVM algorithm take more advantages on the forecast accuracy, but the parameters of SVM model have a great impact on the forecast accuracy. Parameter optimization becomes one of the most important content in the research of SVM [7-8].

Reference [9] uses support vector machine algorithm into forecasting the output power of photovoltaic power generation system, and put forward a conception of photovoltaic power prediction system based on the forecasting algorithm of SVM.

Reference [10] introduces the web search algorithm, genetic algorithm and particle swarm optimization algorithm. After comparing the forecast results of the three different parameter optimization methods, we find the forecast results of particle swarm optimization support vector machine(PSO-SVM) is significantly better than the other two methods.

Reference [11] selects similar days by the indicators of maximum temperature, minimum temperature, maximum humidity, minimum humidity and so on. Then forecasts the

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output power of photovoltaic power generation system by least squares support vector machine (LS-SVM). Proved the LS-SVM can do better at forecast accuracy than neural network algorithm and the normal SVM algorithm.

This article researches the parameter optimization method of quantum particle swarm optimization(QPSO), then introduces QPSO-SVM to the short-term power prediction of the photovoltaic system. The method is validated by a photovoltaic system data of a photovoltaic power station in Wuhan. The results show that QPSO-SVM can do better in speed, precision and stability, which provides reference to the short-term power prediction of the photovoltaic system.

2. The Quantum Particle Swarm Qptimization Algorithm

QPSO algorithm is a new PSO algorithm combines quantum physics theory and the traditional PSO algorithm, which is based on the quantum physics theory, and regards the particles of PSO follow the motion of quantum physics. So we can describe the movement of particles by quantum physics. QPSO-SVM is an improved SVM algorithm which takes advantage of QPSO parameter optimization [12-15].

When describes the particles of PSO by quantum physics, we regard all the particles are moving around an attraction potential center, we record it as $q_i = (q_{i,1}, q_{i,2}, q_{i,3}, \ldots, q_{i,m})$. i is the number of the particles, m is the dimension of the mathematical problem. The coordinate of the attraction potential center is:

$$q_{i,j} = \varphi_{i,j} \cdot p_{i,j} + [1-\varphi_{i,j}] \cdot p_{g,j}, \; j = 0,1, \ldots, m \tag{1}$$

$\varphi_{i,j}$ is a random number uniformly distributed on [0,1], $p_{i,j}$ is the optimal location particles ever reached, $p_{g,j}$ is the optimal location the group of particles ever reached.

In the quantum space the wave function ψ is used to describe the state of particles. The modulus-squared value of the wave function represents the probability density of particles to appear in any place of the space. The formula is as follows:

$$\int_{-\infty}^{\infty} |\psi|^2 dxdydz = \int_{-\infty}^{\infty} Q dxdydz = 1 \tag{2}$$

Q represents the probability of a particle to appear in point (x, y, z). Set a one-dimensional problem for example, assume a single particle at point x in a one-dimensional space. Establish a one-dimensional potential well in the attraction potential center q. By solving the Schrodinger Equation we can get the probability density function Q, and then calculate the position of the particle by Monte Carlo stochastic simulation, the basic evolution equation of this particle in QPSO algorithm is as follows:

$$x = q \pm (L \cdot ln(1/u))/2 \tag{3}$$

L is the characteristic length of the one-dimensional potential well, u is a random number uniformly distributed on [0,1]. For a m-dimensional space, we can assume the attraction potential center is $q_i = (q_{i,1}, q_{i,2}, q_{i,3}, \ldots, q_{i,m})$, and establish a one-dimensional potential well for every attraction potential center in each dimension. We can define a best average location as $P = (P_1, P_2, P_3, \cdots, P_m)$, for n particles in a m-dimensional space, the best average location is:

$$P = [P_1(t), \cdots, P_m(t)] = [\sum p_{i,1}(t), \ldots, \sum p_{i,m}(t)]/n \tag{4}$$

Then the characteristic length of the m-dimensional potential well can be described as:

$$L_{i,j} = 2\alpha \cdot |P_j - x_{i,j}| \tag{5}$$

α is the contraction-expansion coefficient, in this paper α is linearly declining from 1 to 0.5. Combining the (3) and (5), we can finally get the evolution equation of QPSO algorithm:

$$x_{i,j}(t+1) = q_{i,j} \pm \alpha \cdot |p_j - x_{i,j}(t)| \cdot In(1/u_{i,j}) \tag{6}$$

3. Short-term Power Prediction of the Photovoltaic System Based on the QPSO-SVM

3.1. Data Normalization

The original power data cannot be used to predict the output power directly because some data is error or missing. We should add the missing data and correct the significant errors in the data by the adjacent data. Then normalize the data by the equation as follows:

$$x_i^* = (x_i - x_{min})/(x_{min} - x_{min}) \quad (7)$$

x_i^* is the normalized data, x_i is the original data, x_{max} is the maximum data, x_{min} is the minimum data.

3.2. Input and Output Data of Prediction

The data of this paper is according to a photovoltaic power station in Wuhan. Before forecasting we should select similar days for photovoltaic power prediction. In this paper we use grey relation analysis to analyze the climate similarity of historical days and forecast day in terms of photovoltaic power prediction [16-19], first calculating the similar degree of each climate indicators between the historical days and forecast day, then have a weighted sum. At last, select six most similar days and regard them as the historical days.

The input and output data of prediction is as follows:

Input data are the output power data of the historical at each corresponding times and its nearby times; the data of some climate indicators such as temperature, humidity and solar radiation. Output data are the output power data forecasting by SVM of the forecast day.

3.3. Parameter Setting

The main point of SVM prediction is parameter optimization. There are three important parameters of nonlinear support vector regression machine: penalty factor C, non-sensitive loss coefficient ε and the kernel width coefficient of the Gaussian radial basis kernel function σ. Since the prediction is a three-dimensional problem in QPSO-SVM, we set the three parameters as follows:

$$C = |p_{i,1}|,\ C > 0 \quad (8)$$

$$\sigma = |p_{i,2}|,\ \sigma > 0 \quad (9)$$

$$\varepsilon = |p_{i,2}|,\ 0 < \varepsilon < 1 \quad (10)$$

3.4. Prediction Process

The specific calculation steps are as follows:

(1) Set the size of particles $n = 20$, the dimension $m = 3$, and the location of the number i particle in space is $x_i = (x_{i,1}, x_{i,2}, x_{i,3}, \ldots ,x_{i,m})$, $p_i = (p_{i,1}, p_{i,2}, p_{i,3},\ldots,p_{i,m})$is the optimal location particles ever reached, $p_g = (p_{g,1}, p_{g,2}, p_{g,3}, \ldots,p_{g,m})$ is the optimal location the group of particles ever reached, t is the number of current iteration.

(2) Then initialize the location of all particles randomly, calculate the fitness value and the location of each particle. In this paper, the fitness value is the RMSE of the prediction results. Store the fitness value and the location of each particle in function *pbest*, and the fitness value and the location of the group in function *gbest*.

(3) Update the location of each particle by the functions as follows:

$$q_{i,j}(t+1) = \varphi_{i,j}(t) \cdot p_{i,j}(t)+[1-\varphi_{i,j}(t)] \cdot p_{g,j}(t) \quad (11)$$

$$\alpha(t+1) = \alpha_{max} - t \cdot (\alpha_{max} - \alpha_{min}) / \alpha_{max} \quad (12)$$

$$x_{i,j}(t+1) = q_{i,j}(t) \pm \alpha(t) \cdot |P_j(t) - x_{i,j}(t)| \cdot In(1/u_{i,j}(t)) \quad (13)$$

Calculate the fitness value and the location of each particle after updating, and then update the function *pbest* and *gbest* with the current best location.

(4) Judge the results, if the results satisfy the termination condition, stop update and output the best result. Or return to step 3.

(5) After getting the appropriate parameters, input them in SVM for the forecasting process.

The flow chart is showed in Figure 1.

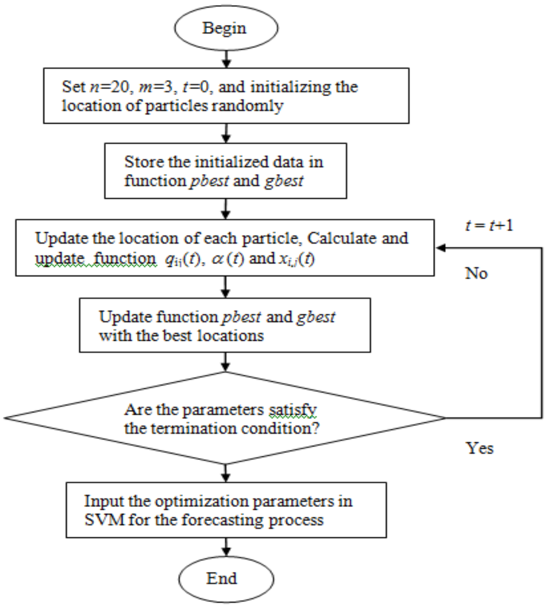

Figure 1. The Prediction Process of QPSO-SVM

4. Numerical Example

In this paper the data is from a photovoltaic power station in Wuhan, the monitoring interval is 10min. We take the data of six historical days in which the climate conditions is most similar to the forecast day for historical data, to forecast the output power of the forecast day. Code the GA-SVM, SPSO-SVM and QPSO-SVM by MATLAB. Forecast the output power of the photovoltaic system by the three parameter optimization methods as above, and then do a comparison of them. The results of prediction is showed in Table 1, the prediction step is 10min.

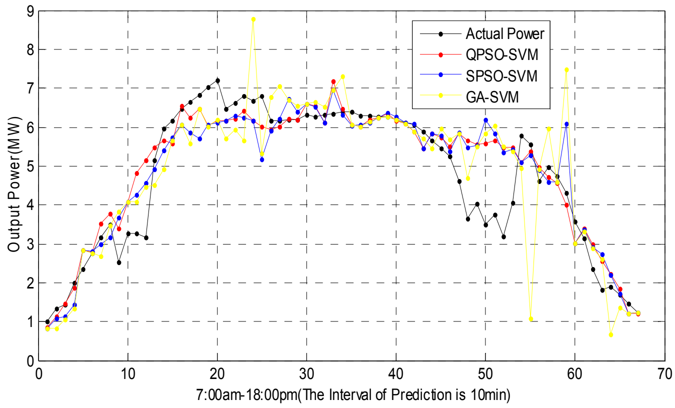

Figure 2. The Prediction Results of Three Methods

The figure of the prediction results shows that the prediction results of QPSO-SVM are the most similar to the actual power, and the GA-SVM have the least similar result. Analyzing the results in Table 1, we can find that the number of the forecasting time in which the MRE is below 20% is 53 of the QPSO-SVM method, and the number of SPSO-SVM is 49, 45 MRE results of the GA-SVM is under 20%

Calculate the average relative error, mean absolute error mean square error and root mean square error of each method according to the prediction results.

Table 1. The Prediction Errors

Prediction Methods	The Prediction Errors			
	MAE (MW)	MRE (%)	MSE (MW)2	RMSE (MW)
QPSO-SVM	1.5668	13.88	5.3045	2.3031
SPSO-SVM	1.7639	15.04	6.2389	2.4978
GA-SVM	2.3283	19.51	10.9117	3.3033

We can see clearly from the results showed above. When we have parameter optimization by the three ways, QPSO algorithm can find better parameters and the prediction results of QPSO-SVM are more similar to the actual data.

By analysis the forecasting results we can find that the relative error of prediction in two periods is large. It's because there were many fluctuations of the climate conditions in the forecast day in fact, so the output power of the photovoltaic power station fluctuated in the two periods, but the forecasting curves are usually smooth.

Overall, the average relative error of three parameter optimization methods is below 20%, they all have certain industrial reference values. But the QPSO-SVM takes more advantages in accuracy. And because the state of motion of the particles in QPSO is only described by displacement, the model of QPSO-SVM is simpler than the other two methods, so computational complexity and computational speed of QPSO-SVM is also better than the other two methods.

5. Conclusion

This paper uses QPSO algorithm for parameter optimization of SVM, and applies QPSO-SVM into the short-term power prediction of the photovoltaic system. The test data is from a photovoltaic power station in Wuhan, after comparing with GA-SVM and SPSO-SVM, we find the QPSO-SVM algorithm can do better at accuracy and computational speed. The results certify that QPSO-SVM has feasibility and good performance in the short-term power prediction of the photovoltaic system.

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