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A Novel Short-term Multi-input-multi-output Prediction Model of Wind Speed and Wind Power with LSSVM Based on Quantum-behaved Particle Swarm Optimization Algorithm

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With the rapid development of wind power, the installed capacity of wind power is also growing continuously. The intermittency and uncertainty of wind power may pose danger on the safety of the power system, thus Research of short-term load forecasting has important practical application value in the field of power network dispatching. The keys of wind power forecasting are the forecasting model selection and model optimization. In this paper, the least squares support vector machine (LSSVM) is chosen as the wind speed and the wind power prediction model and quantum-behaved particle swarm optimization (QPSO) algorithm is used to optimize the most important parameters which influence the least squares support vector machine regression model. In the proposed QPSO-LSSVM, the kernel parameter σ and regularization parameter γ are considered as the position vector of particles and quantum mechanics is introduced in particle swarm optimization (PSO) algorithm to effectively solve the contradiction between expanding search and finding optimal solution. A multi-input-multi-output (MIMO) short-term prediction model is built and applied in a wind farm of Gansu province in order to predict wind speed and wind power. For comparative study, PSO-LSSVM model and SVM model are used for forecasting, meanwhile, several error indicators are selected to analyze the results of the three models. Prediction analysis results show that the QPSO-LSSVM model can achieve higher prediction accuracy and confirm the effectiveness and feasibility of the method.

1. Introduction

The worldwide wind capacity reached approximately 432.4 GW by the end of 2015, out of which 63 GW were added in 2015. In particular, China installed 145.1 MW by the end of 2015, which becomes the country with the most installed wind energy capacity (Qian et al., 2016). Despite the environmental benefits of wind power, it has intermittent and uncertainty nature, which could affect the security and reliability of power system.

Load forecasting is susceptible for a wide variety of facts, such as climate conditions and previous load demand data. At present, there are two methods of prediction of wind power generally according to different data source, one is statistical learning method (Sideratos et al., 2007), the other is physical method. Statistical learning method which is used most commonly builds statistical learning model through historical data of wind farm and measurement data around wind farm, and the statistical learning model includes time series analysis (TSA) model, artificial neural network (ANN) model, support vector machine (SVM) modelgrey model, data mining model, etc (Brown et al., 1984). However, most of the factors which influence the short-term power load have uncertainty, complexity and strong nonlinearity, there are also some limitations in the traditional linear fitting prediction methods (Chitsaza et al., 2015). Despite ANN in short-term load forecasting area has obtained certain research results, it has defect of poor generalization ability and falling into local minimum value easily (Chen et al., 2014). Recently, SVM which is a kernel-based machine learning method is a promising method for pattern classification and regression proposed by Vapnik, based on statistical learning theory and structural risk minimization, and it has been proved to be better than artificial neural network method and other methods in power load forecasting filed (Zhang et al., 2016). Least squares support vector machine (LSSVM) which changes inequality constraints into equality constraints though quadratic

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programming method, adopts square sum of error of loss function as the experience loss of the training sample set, converts the quadratic programming problem into linear equations is an improved standard support vector machine (Yusof et al., 2013).
The forecasting performance of the LSSVM model largely depends on the values of its two parameters, which are the bandwidth of the Gaussian RBF kernel σ and the punishment factor γ. Motivated by this problem, many researchers have drawn ideas from intelligent algorithms. Although genetic algorithm (GA) which does not depend on mathematical model of the problem has been used to select parameters of LSSVM in many fields, it is used rarely in multivariable function optimization because of complex operations such as selection, crossing and mutation. However, ant colony optimization (ACO) has the features of positive feedback, high accuracy, robustness, strong parallelism, it is easy to sink into local convergence, and failing to find the true global optimal solution. Particle swarm optimization (PSO) is originally attributed to Kennedy and Eberhart, who were inspired by the behavior of bird swarms in 1995. However, PSO have been used extensively for various multi-objective optimization problems, there have premature convergence and local optimal solution problems. Given this, many attempts have been made to improve the performance of the PSO (Duan et al., 2012). Sun et al. introduced quantum theory into PSO and proposed a quantum-behaved PSO (QPSO) algorithm, which is a global search algorithm that, in theory, is guaranteed capable of finding good optimal solutions in the search space. So QPSO developed quickly, and got good application in many optimization problems (Li et al., 2015). In this paper, QPSO is employed to optimize the parameters of LSSVM, and a multi-input-multi-output (MIMO) short-term wind speed and wind power prediction model is established. The data of wind farm in Jiuquan city, Gansu province was taken as the sample to be analyzed for short-term prediction one day ahead, and a promising result can be concluded (Soebiyan et al., 2017).

2. Parameter selection of LSSVM based on QPSO

2.1 LSSVM

SVM is a kind of newly developed machine learning method based on statistical learning theory. Consider a l-sample training set, $\{x_i, y_i\}_{i=0}^{l}$, with $x_i \in R^n$ and $y_i \in R$, map samples to high-dimensional feature space by nonlinear function $\emptyset(\mathrm{x})$, structure the optimal decision-making function by using the principles of structural risk minimization. LSSVM model for regression takes the form as follows:

$$f(x) = w^T \cdot \phi(x) + b \tag{1}$$

Where, w is a weight vector, b is a bias, the purpose of solving the problems of regression estimation is to obtain w and b by minimizing a regularization function with risk, the optimal objective function can be written as the following form:

$$\begin{aligned} &\min \mathrm{J}(\mathrm{w},\zeta) = \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{i=1}^{l} \xi_i^2 \\ &s.t. \quad y_i = w \cdot \phi(x_i) + b + \xi_i, i = 1, 2, \cdots l \end{aligned} \tag{2}$$

Where, γ denotes regularization parameter and ξ_i denotes slack variable, model coefficients a, b can be obtained through solving Lagrange function, then the function estimation of LSSVM can be written as the following form:

$$f(x) = \sum_{i=1}^{l} \alpha_i K(x, x_i) + b \tag{3}$$

Kernel function can be determined under Mercer conditions as follows:

$$K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j) \tag{4}$$

Most widely used kernel functions is RBF and RBF has been carried out as follows:

$$k(x_i, x_j) = \exp(-\frac{\left\|x_i - x_j\right\|^2}{2\sigma^2}) \tag{5}$$

Where, σ denotes the radius of kernel function. From the estimating function mentioned above, the way of mapping the initial input data into a high-dimensional space depends on kernel function σ, and the regularization parameter γ is used for balancing between training error and model complexity. So appropriate parameters selection is crucial to the learning performance and generalization ability of LSSVM.

2.2 Particle swarm optimization

In PSO, a group of particles is composed of m particles in D dimension space where the position vector of the particle i is $x_i = (x_{1i}, x_{2i}, \dots, x_{iD})$ and the speed vector is $v_i = (v_{1i}, v_{2i}, \dots, v_{iD})$. The speed and position of each particle are changed in accordance with the following equation:

$$v_{id}^{j+1} = wv_{id}^{j} + c_1 r_1 (p_{id}^{j} - x_{id}^{j}) + c_2 r_2 (p_{gd}^{j} - x_{id}^{j}) \tag{6}$$

$$x_{id}^{j+1} = x_{id}^{j} + x_{id}^{j+1} \tag{7}$$

where *i*=1, 2, …, m, *d*=1, 2, …, D, m is the particle size, p_{id}^{i} is the dth dimension component of the pbest which is the individual optimal location of the particle i in the jth iteration; p_{id}^{i} is the dth dimension component of the gbest which is the optimal position of all particles in the jth iteration; *w* is the inertia weight coefficient, c_1 and c_2 are learning factors, r_1 and r_2 are random numbers in the range of 0-1.
W which balances the global and local exploitation abilities of the swarm is the inertia weight, it is critical for PSO. A large w can facilitate exploration but slow down particle convergence. Conversely, a small w can promote fast convergence but easy to lead to local optimal. The most popular algorithm for controlling inertia weight is linearly decreasing inertia weight which is widely used to improve the performance of PSO, but this approach has a number of drawbacks. Several adaptive algorithms for tuning inertia weight have been presented. In this paper, the method of nonlinearly decreasing inertia weight to tune the value of w for further performance improvement is proposed as follows:

$$w = w_{\max} - (w_{\max} - w_{\min}) \times (t-1)^2 / (t_{\max} - 1)^2 \tag{8}$$

where w_{max} and w_{min} are the maximum and minimum values of w, respectively, t is the current iteration number, t_{max} is the maximum iteration number.

2.3 Quantum-behaved particle swarm optimization

Quantum mechanics is introduced to overcome the problem of local convergence of PSO algorithm, and QPSO algorithm is proposed by Sun et al.
Particles move according to the following iterative equation:

$$x_{i,j}(t+1) = p_{i,j}(t) + \alpha \left| mbestj(t) - x_{i,j}(t) \right| \cdot \ln(1/u) \quad \text{if k} \geq 0.5 \tag{9}$$

$$x_{i,j}(t+1) = p_{i,j}(t) - \alpha \left| mbestj(t) - x_{i,j}(t) \right| \cdot \ln(1/u) \quad \text{if k} < 0.5 \tag{10}$$

where

$$mbest_j(t) = \frac{1}{M} \sum_{i=1}^{M} pbest_{i,j}(t) \tag{11}$$

$$p_{i,j}(t) = \varphi_{i,j}(t) \cdot pbest_{i,j}(t) + (1 - \varphi_{i,j}(t)) gbest_j(t) \tag{12}$$

where $mbest$ is the mean best position defined as the mean of all the pbest positions of the population, M is the size of particle swarm, k, u, φ are random numbers generated using uniform probability distribution in the range (0, 1), α is the contraction-expansion coefficient which is tuned to control the convergence speed of particles, to be sure, the parameter α can be controlled by either fixing value or varying the value in the search of the algorithm. Satisfactory results for most benchmark functions have been achieved when α is setting in the range (0.5, 0.8) (Sun et al., 2012). Although, fixing the value of α is sensitive to population size and the maximum number of iterations, the problem can be overcome by using a time-varying coefficient. In this present paper, let α decrease linearly from α_1 to α_0, of course α_0 is smaller than α_1, so α is computed as follows:

$$\alpha = \alpha_1 - (t-1) \times (\alpha_1 - \alpha_0) / (T-1) \tag{13}$$

where α_0 which is set to 0.5 generally is the initial value of α, α_1 which is set to 1 is the final value of α, t is the current iteration number, and T is the maximum iteration number.

2.4 Parameter optimization of LSSVM based on QPSO

The objective function is defined as the following form:

$$\begin{aligned} &\min\ f(\gamma,\sigma)=\sum_{i=1}^{N}(y_i-\hat{y}_i)^2 \\ &s.t. \quad \gamma\in[\gamma_{\min},\gamma_{\max}] \\ &\qquad\ \ \sigma\in[\sigma_{\min},\sigma_{\max}] \end{aligned} \tag{14}$$

Where, y_i denotes the desired output value of sample, $\hat{y}_i$ denotes the raining output value, N is the number of the sample, γ_{min} is the minimum regularization parameter, γ_{max} is the maximum regularization parameter, σ_{min} is the minimum kernel parameter, σ_{max} is the maximum kernel parameter. The purpose of parameter optimization method is to search for a set of parameters σ and γ to minimize the objective function by iterative process. Steps of optimizing parameters by QPSO are as follows:

1. Initialize the parameters of QPSO, such as the size of particle swarm, the maximum iteration number, and the ranges of parameters σ and γ, and then randomly produce a set of σ and γ in the given value ranges by a uniform probability distribution function.
2. Calculate the fitness value of particle by Eq. 14.
3. Calculate the mbest and $p_{i,j}(t)$ by using Eq. 11 and Eq. 12.
4. Compare each particle's fitness with the pbest value. If the current value is better than the pbest value, then set the current value as the pbest value and the *pbest* location as the current location.
5. Update the position of the particles by Eq. 9 and Eq. 10.
6. Output the best parameter σ and γ if when the fitness value is less than the set value or the current iteration number reach to the maximum number of iterations, otherwise, go to step 2.
7. Build model based on QPSO-LSSVM using optimal parameters σ, γ and training sample.

3. Prediction model

Consider m dimensions input variable X and n dimensions output variable Y compose data points $\{X_i, Y_i\}$, where i=1, 2, …, q, MIMO-LSSVM model can be defined as the following form:

$$Y_j(x)=\sum_{i=1}^{q}a_{ij}k(x_j+x_{ij})+b_j \tag{15}$$

Where, i=1, 2, …, q, j=1, 2, …,n. then n sets optimal parameters σ, γ can be obtained, the objective function of different variables can be written as the following form:

$$\min\ f(\gamma_j,\sigma_j)=\frac{1}{q}\sum_{i=1}^{q}(y_{ij}-\hat{y}_{ij})^2 \tag{16}$$

Where, i=1, 2, …, q, j=1, 2, …, n, y_{ij} is despired output of variable sample j, $\hat{y}_{ij}$ is prediction output based on LSSVM model of variable sample j. The optimal parameters which can be got by iteration of improved ant colony algorithm and calculation of training samples are used in LSSVM prediction model, then model of wind farm prediction has been completed.

The structure of short-term forecasting model of wind farm can be composed of the following three parts:

1. Input section: the input section is mainly the source of data, including historical wind speed, wind power, wind direction, rotor speed of wind turbine, pitch angle of wind turbine and environmental climate conditions of temperature, air pressure, relative air humidity, etc. Before input into the prediction model, the sample data should be filtered and normalization arranged.
2. Internal logic section: MIMO prediction model of wind farm based on QPSO-LSSVM is built and relevant program is carried out in this section. firstly, the parameters of least squares support vector machine and quantum-behaved particle swarm optimization algorithm are initialized, then the parameters σ, γ of LSSVM based on QPSO proposed in this paper are optimized considering minimum square sum of regression error as fitness, the optimization steps are used as shown in chapter 2. At last, the LSSVM regression model using optimized parameters is re-established.
3. Output section: the prediction output of wind speed and wind power at wind farm has been obtained after the program is executed, and several common error indicators are analyzed in this section. In this paper, speed and load are forecasting objects, a 8 input-2 output forecasting model is built.

4. Results and analysis

The data from September 1, 2015 to September 29, 2015 in Guazhou County, Jiuquan city Gansu province is selected in this paper, 11_06F Sample wind turbine which is 1.5 MW doubly fed induction generator (DFIG) is took as example. The parameters of the proposed DFIG are as follows: rated power is 1.5MW, cut-in wind speed is 2.8m/s, cut-out speed is 23m/s, rated speed is 11m/s, the number of rotor blade is 3. The data including wind speed, wind direction, wind power, rotor speed of wind turbine, pitch angle of wind turbine, temperature, air pressure and relative air humidity around the wind turbines have been collected every 10 min, thus there are 4320 groups data accordingly, then the data after eliminated significant error and processed by normalization should be taken as the training sample, meanwhile, and the data from September 30, 2015 should be taken as test sample, wind speed and load one day ahead are predicted by prediction model based on QPSO-LSSVM proposed in this paper. Parameters of the proposed model are set as follows: M=20, the maximum iteration times Nmax=260. Kernel function parameter σ, and the regularization parameter, γ can be optimized by QPSO algorithm through matlab2012b: $\gamma = [24.86{,}496.125]$, $\sigma = [0.1238.921]$. In addition, PSO-LSSVM and single SVM are applied to forecast, it can be found that it began to convergence at 40 times gradually by QPSO-LSSVM method proposed in this paper compared with more than 150 times by PSO-LSSVM method. The results of the prediction of wind speed and wind power under the three methods are compared in the following, as shown in Figure (a) and (b).

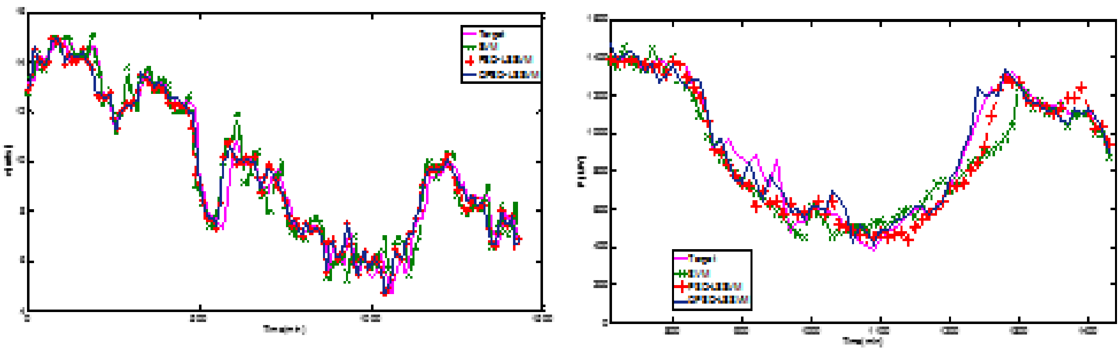

Figure 1: The results of wind speed forecasting under the three models and (b) The results of wind power forecasting under the three models

As can be seen from Figure 2 and Figure 3, although the three methods can be able to track the target output of wind speed and load, the curve of QPSO-LSSVM method is closer to the target curve compared than the other two methods whether speed or load. In order to analysis in detail, several error indicators can be selected as follows:

$$SSE = \sum_{j=1}^{n} (y_j - \hat{y}_j)^2$$

$$MSE = \frac{1}{n}\sqrt{\sum_{j=1}^{n} (y_j - \hat{y}_j)^2}$$

$$MAPE = \frac{1}{n}\sum_{j=1}^{n} \left| \frac{y_j - \hat{y}_j}{y_j} \right|$$

$$MSPE = \frac{1}{n}\sqrt{\sum_{j=1}^{n} ((y_j - \hat{y}_j)/y_j)^2} \tag{17}$$

Where, SSE denotes sum of squares of absolute error, MSE denotes mean square error, MAPE denotes mean absolute percentage error, MSPE denotes mean square percent error, y_j is the target value of point j, $\hat{y}_j$ is the prediction value of point j, n is the number of prediction points. The tracking errors of wind speed and wind power under the three methods are compared in the following, as shown in Table 1 and Table 2.

As can be seen from Table 1, when QPSO is selected to optimize parameters of LSSVM, the tracking errors of wind speed can be significantly reduced compared with PSO-LSSVM and single SVM methods, Among the errors, MAPE is 4.52% lower than PSO-LSSVM forecasting method by 0.91% and SVM method by 2.28%. As can be seen from Table 2, the tracking errors of wind power prediction one day ahead with QPSO-LSSVM also can be significantly reduced compared with PSO-LSSVM and single SVM methods, MAPE is 3.81%

lower than PSO-LSSVM forecasting method by 1.3% and SVM method by 2.92%. So QPSO-LSSVM has a better performance on forecasting accuracy compared with the other methods.

Table 1: The tracking error comparison of different wind speed forecasting methods

different forecasting method	e_{SSE}	e_{MSE}	e_{MAPE}	e_{MSPE}
SVM	80.4724	0.0623	0.0680	0.0078
PSO-LSSVM	65.7866	0.0541	0.0543	0.0066
QPSO-LSSVM	46.7167	0.0456	0.0452	0.0059

Table 2: The tracking error comparison of different wind power forecasting methods

different forecasting method	e_{SSE}	e_{MSE}	e_{MAPE}	e_{MSPE}
SVM	1.3136e+06	7.9592	0.0673	0.0082
PSO-LSSVM	7.0863e+05	5.6120	0.0511	0.0064
QPSO-LSSVM	3.9145e+05	4.1711	0.0381	0.0051

5. Conclusion

8 input-2 output short-term forecasting model of wind speed and wind power based on LSSVM method has been built. A new regression model of LSSVM was put forward based on QPSO, QPSO was used to optimize the kernel parameter σ and regularization parameter γ, which was proved to have better accuracy. Simulation and case analysis results show that the proposed forecasting model can obtain favourable performance and better forecasting accuracy compared with PSO-LSSVM method and single SVM method. So the presented approach is suitable for short-term load forecasting and speed forecasting.

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