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Short-term wind speed forecasting based on improved ant colony algorithm for LSSVM

Yanan Li[1] · Peng Yang[1] · Huajun Wang[1]

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Abstract

In this paper, a least squares support vector machine (LSSVM) model with parameter optimization is proposed for solving the problem that the forecast accuracy of neural network model and support vector machine model is not desirable for the sake of improving short-term wind speed forecast accuracy further. The parameters of LSSVM are optimized by the improved ant colony algorithm. Firstly, the parameters of LSSVM are regarded as the position vector of ants. Another argument is that the global search is carried out by selecting some ants randomly from the ant colony to guide the whole ant colony, while searching the optimal ant neighborhood. Furthermore, the optimal parameters of the model are obtained, and the wind speed prediction model of LSSVM is established through parameter optimization. Taking a wind farm in North China as an example, the collected wind speed data were taken in predicted experience, besides the results were compared with the BP neural network model and the LSSVM model. The results show that this model has significant advantages compared with the other two models and has high practical significance.

Keywords Short-time wind speed forecast · Least squares support vector machine · BP neural network · Ant colony algorithm

1 Introduction

Since the energy and environmental problems have become increasingly prominent, wind energy as an important renewable energy resource has been paid more and more attention in recent years by virtue of its widely distributed, pollution-free and renewable [1]. However, due to the characteristics of randomness and volatility of wind power generation, large-scale wind power access to power grid will cause great impact on the power system is not conducive to the maintenance and smooth operation of the power system. Wind speed perturbation easily causes great changes of voltage and frequency of the power grid system, seriously the power system will be instable [2]. The study about short-term forecast on wind speed and power of wind farms is beneficial to stable power system operation, which prompting the relevant dispatching department to adjust the plan according to the forecast result, so as to reduce the influence of intermittent wind power [3].

At present, many experts at home and abroad have done a lot of research on short-term wind speed forecasting of wind farms. Wind speed forecast can be classified into three categories according to technology: digital weather forecast, statistical method and neural network forecasting method [4]. In recent years, artificial neural network (ANN) has made some achievements in wind speed forecast. However, ANN has some weakness. In fact, it is difficult to determine the network structure, besides over-learning and easily fall into the local minimum [5,6]. The support vector machine (SVM) method based on statistical theory can solve the problem of small sample and non-linearity well. It is proved to be better than artificial neural network and other methods in wind speed forecast. Hu Qian et al. proposed an integrated learning model based on Adaboost to forecast the short-term wind speed and obtain desirable results for solving the problem that the traditional single SVM model is not accurate [7,8]. The least squares support vector machine (LSSVM) replaces the inequality constraints with equality constraints on the basis of SVM, which avoids the time-consuming quadratic programming problem, so it is a powerful tool for nonlinear system modeling and prediction [9].

In the LSSVM model, the parameter penalty factor and kernel function have great influence on the forecast effect

✉ Yanan Li
quancuyongwei@yeah.net

1 College of Control Science and Engineering of Hebei University of Technology, Tianjin, China

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of the model. Therefore, it is the key to forecast the wind speed by determining the reasonable LSSVM penalty factor and kernel function [10]. Fang Biwu and others the parameters of LSSVM to achieve short-term wind speed forecast by improving firefly algorithm [11–13]. Zhang et al. adopted genetic algorithm to optimize the LSSVM parameters. But the genetic algorithm is not suitable for the whole modeling because of the complex operation. Some scholars optimized LSSVM by using genetic algorithms and other bionic algorithm. Chappelle proposed gradient descent method to optimize LSSVM parameters. Despite the fact that the efficiency of genetic algorithm has been significantly improved, this approach is easy to fall into the demerit of local optimum. Sun Bin and so on optimized the LSSVM parameters through the particle swarm optimization algorithm, and then forecasted the wind time series which reconstructed phase space by using optimized LSSVM model. At present, there is no definite conclusion on which kind of optimization method can optimize the LSSVM parameter to forecast the wind speed better. In practically, the parameters are determined by experience for the most part, which may lead to the problem of low forecast accuracy due to inappropriate parameters selection [14]. To solve this problem, the LSSVM parameters are optimized by improved ant colony algorithm for the sake of establishing the model of optimized parameters LSSVM wind speed forecast [15]. The correctness of the proposed algorithm is verified by comparing with the BP neural network model and the LSSVM model without parameter optimization.

2 Least squares support vector machine regression model

Support vector machine (SVM) is a very powerful machine learning method built on the basis of Vapnik's statistical learning theory. It can solve the small sample, nonlinear, high dimension and local minimum problems [16]. It has become one of the research focuses in the field of machine learning and successfully applied to classification, function approximation and time series prediction [17]. However, SVM faces some problems in solving a large sample problem, such as the two quadratic programming (QP) problem, the traditional algorithm of matrix multiplication kernel function in each iteration, and the matrix of kernel memory occupied with the sample number is increasing square [18]. Because of the accumulation of iterative error, the accuracy of the algorithm cannot be accepted. Least squares support vector machine is an improved support vector machine. Compared with the standard SVM model, this method has two obvious advantages: the first one is that inequality constrained by equality constraints instead of the standard SVM algorithm; and the second is to solve the two programming problem is transformed into solving linear equations directly [19].

The training process of least squares support vector machines also follows the principle of structural risk minimization. Inequality constraints are changed into equality constraints. Change the empirical risk from one side of the variance to the two. The two-order programming problem is transformed into a system of linear equations. It avoids the insensitive loss function and greatly reduces the computational complexity, and the computation speed is higher than the general support vector machines.

Least squares support vector machine is an improvement of support vector machine. It takes the form of equality constraints, uses the least squares linear system as the loss function, and obtains the final solution by solving linear equations. The basic principles of the model are as follows:

Give a set of sample datasets: (x_i, y_i), $i = 1, 2, \ldots$n, $x \in R^n$, $y \in R$. Where x_i is the ith input vector, y_i is the ith output vector. The sample is mapped into a high-dimensional space by a nonlinear function, and then the linear regression is performed. The regression function is:

$$f(x) = w^T \varphi(x) + b$$

where w is the weight vector, b is the deviation. When LSSVM performs function regression, the optimization goal is:

$$\min J(w, \zeta) = \frac{1}{2} w^T w + \frac{1}{2} C \sum_{i=1}^{m} \zeta^2$$
$$\text{s.t.} \quad y_i = w\varphi(x) + b + \xi_i, \quad i = 1, 2, \ldots m$$

where C is the error penalty function, ξ_i is the slack variable.

Construct the Lagrange function L:

$$L(w, b, \zeta, a) = \frac{1}{2} w^T w + \frac{1}{2} C \sum_{i=1}^{m} \zeta_i^2 - \sum_{i=1}^{m} a_i \{w^T \varphi(x_i) + b + \zeta_i - y_i\}$$

where a_i is the Lagrangian multiplier.

According to KKT conditions:

$$\begin{cases} \frac{\partial L}{\partial w} = 0 \to w = \sum_{i=1}^{m} a_i \varphi(xi) \\ \frac{\partial L}{\partial b} = 0 \to \sum_{j=1}^{m} a_i = 0 \\ \frac{\partial L}{\partial \zeta_i} = 0 \to a_i = C\zeta_i \\ \frac{\partial L}{\partial ai} = \to w^T \varphi(xi) + b + \zeta_i - y_i = 0 \end{cases}$$

The kernel function can be determined according to Mercer's condition.

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

Then the LSSVM function is estimated as:

$$f(x) = \sum_{i=1}^{m} a_i K(x, x_i) + b$$

In this paper, radial basis function (RBF) is used as kernel function.

$$K(x, xi) = \exp\{-\|x - xi\|^2 / 2\sigma^2\} \tag{1}$$

where σ is the width of the kernel function.

According to the basic principle of LSSVM model, the main parameters are kernel function parameter and penalty parameter C, which have great influence on the learning and generalization performance of LSSVM. In this paper, the parameters σ and C are optimized by improved ant colony algorithm in order to improve the forecast performance of the LSSVM model.

3 Improved ant colony algorithm

Ant colony algorithm (ACO) is a probabilistic algorithm for finding optimal paths. This algorithm has the characteristics of distributed computation, information positive feedback and heuristic search. It is essentially a heuristic global optimization algorithm in evolutionary algorithms [20].

Compared with other optimization algorithms, ant colony algorithm has the following characteristics [21]:

Firstly, by using the positive feedback mechanism, the search process converges continuously and finally approaches the optimal solution.

Secondly, each individual can change the surrounding environment by releasing information, and each individual can perceive the real change of the surrounding environment, and the individuals communicate indirectly through the environment.

Thirdly, the search process uses distributed computing, and multiple individuals do parallel computing simultaneously, which greatly improves the computing power and efficiency of the algorithm.

Fourthly, the heuristic probability search method is not easy to fall into the local optimum, and it is easy to find the global optimal solution.

The traditional ant colony algorithm is to solve the discrete optimization problem, while the optimization of LSSVM model parameters is the solution of continuous optimization problem. Consequently, we need to improve the ant colony algorithm. Suppose we consider the following continuous optimization problem:

$$\begin{aligned} y = \min f(X),\ & X = (x1, x2, \ldots, xd) \\ \text{s.t.} \quad & X \in [L, U] \end{aligned} \tag{2}$$

In the traditional ant colony algorithm, the ants' pheromone is reflected in the path between discrete points. The improved ant colony algorithm proposed in this paper shows that the ant colony chooses its path by judging the concentration of pheromone in a certain area. The pheromone is attached to the individual of the ant colony, and the greater the concentration, the greater the attractiveness of the individual to the ant in the ant colony.

3.1 Initialize ant colony location and pheromone

Firstly, set the ant colony size as N and distribute the ant colony in the solution space randomly. Then the initial pheromone size of ant i is determined by different optimization problem according to the distribution of ants' initial position.

$$\Delta\tau(i) = \exp(-f'(xi)) \tag{3}$$

For ants' initial position $X_i(x_{i1}, x_{i2}, \ldots x_{id})$, $i = 1, 2, \ldots, N$, when $f(X_i) \geq 0$, according to the above equation, we know that $\Delta\tau(i)$ $\in$(0,1], when $f(X_i)$ is infinite, the pheromone concentration will be infinitely close to zero. Therefore, the fitness $f(x_i)$ should be amended.

$$f'(X_i) = \begin{cases} f(X_i)/avg, & avg > avg0 \\ f(X_i), & \text{otherwise} \end{cases} \tag{4}$$

where avg is the mean value of $f(X_i)$, $f(X_i)$ and $f'(X_i)$ are the fitness values before and after correction respectively.

3.2 Construction of ant colony

This paper establishes two rules for the ant search process. One is to move the ants except the optimal ant to the target individual, so we call it global big step search, and the other is to make the optimal ants search the local step in the neighbor area. Specific rules are as follows:

Rule 1 First of all, chooses p individuals randomly from the ant colony of size N. Secondly, the individual with the largest pheromone concentration in the extracted individual is calculated as the target individual $X_{obj.}$

$$X_{\text{obj}} = \begin{cases} X_j, & \tau(X_i) < \max(\tau(X_j)) \\ X_{\text{best}}, & \text{otherwise} \end{cases} \tag{5}$$

where X_{best} represents the optimal solution obtained in the last iteration.

The greater pheromone of the ants, the greater their attractiveness to other ants, as a result, the ant moves to the target ants according to the following formula.

$$X_i + 1 = (1 - \lambda)X_i + \lambda X_{\text{obj}} \quad (6)$$

Rule 1 is helpful to increase the searching randomness in early iteration period and accelerate the convergence speed in later period.

Rule 2 An ant X_{obj}, which is the optimal solution in the iterative process, is used to refined local search in its neighbor area according to formula (7) and (8).

$$X_{\text{best}} \begin{cases} X', & f(X_i') < f(X_{\text{best}}) \\ X_{\text{best}}, & \text{otherwise} \end{cases} \quad (7)$$

$$X_i' = X_{\text{best}} \pm h \cdot \delta \quad (8)$$

where $\delta = 0.1 \times \text{rand}()$, "$\pm$" is depended on following formula.

$$X_{\text{best}}' = X_{\text{best}} + (X_{\text{best}} \cdot 0.01) \quad (9)$$

If $f(X_{best}') \le f(X_{best})$, then take "+", otherwise take "$-$". h is the dynamic search step, and is updated as follows:

$$h = (h_{\max} - (h_{\max} - h_{\min})'\text{best}) \cdot \frac{i_{\text{ter}}}{i_{\text{termax}}} \quad (10)$$

where h_{max} and h_{min} is the initial set constant, i_{termax} is the maximum number of iterations, i_{ter} is the current number of iterations.

3.3 Pheromone update strategy

After completing the global search and the local search, the pheromone τ *(i)* of the ant i is updated as follows:

$$\tau(i) = (1 - \rho)\tau(i) + \Delta\tau(i) \quad (11)$$

where ρ is the pheromone volatility.

4 Optimization of LSSVM parameters based on ant colony algorithm

Define the objective function as:

$$\min f(C, \sigma) = \sum_{i=1}^{M} (y_i - \hat{y}_i)^2$$
$$s.t. \begin{cases} C \in [C_{\min}, C_{\max}] \\ \sigma \in [\sigma_{\min}, \sigma_{\max}] \end{cases} \quad (12)$$

where y_i is the ith sample output value and $\hat{y}_i$ is the algorithm forecast value.

Searching a set of suitable (C, σ) to minimize the equation mentioned above through the improved ant colony algorithm, that is to complete the optimization.

The process of LSSVM parameter optimization is as follows:

Step 1: Define the training sample set and test sample set according to the collected wind speed data.
Step 2: The LSSVM forecast algorithm, as shown in Eq. (1), is established for the parameters such as ant location and population number defined by improved ant colony algorithm.
Step 3: Calculate the fitness value and pheromone concentration of each ant.
Step 4: Select the p ants in the population randomly and find out the optimal position of them as X_{obj}.
Step 5: Make the non-optimal ant move to the optimal ant position and perform global search.
Step 6: Local searching on the optimal ant to update the pheromone concentration of each ant.
Step 7: Determine if the iteration condition is satisfied, if it is satisfied, output (C, σ), if not, return step four to continue the loop.

5 Short-term wind speed forecast of MACO–LSSVM

5.1 Selection of forecast error index

In this paper, the mean squared error MSE and mean relative error MRE are used to evaluate the forecast results.

$$\text{MSE} = \sqrt{\frac{i}{N} \sum_{i=1}^{N} \left|\hat{y}(i) - y(i)\right|^2} \quad (13)$$

$$\text{MRE} = \frac{1}{N} \sum_{i=1}^{N} \frac{\hat{y}(i) - y(i)}{y(i)} \times 100\% \quad (14)$$

where y_i is the actual value, $\hat{y}_i$ is the forecasted value, N is the number of samples.

5.2 Wind speed forecast experiment

The wind speed data series of a wind farm in North China in October, 2013 are taken as the experimental sample, which is sampled once an hour during continuous 300 h. The 300-hour wind speed data is used to forecast the wind speed one hour ahead of time. The data of the first 250 h are used as the training samples and the last 50 h as the test samples. Based on the experimental data, the proposed algorithm is compared with the BP neural network model and the LSSVM model without parameter optimization. The parameters of the MACO-LSSVM are as follows: the ant colony scale $N=10$, the maximum iteration $i_{termax}=200$, the penalty function error $C \in [1, 10{,}000]$ and the kernel function parameter $\sigma \in [0.1, 10]$. The optimization curve of parameters C and

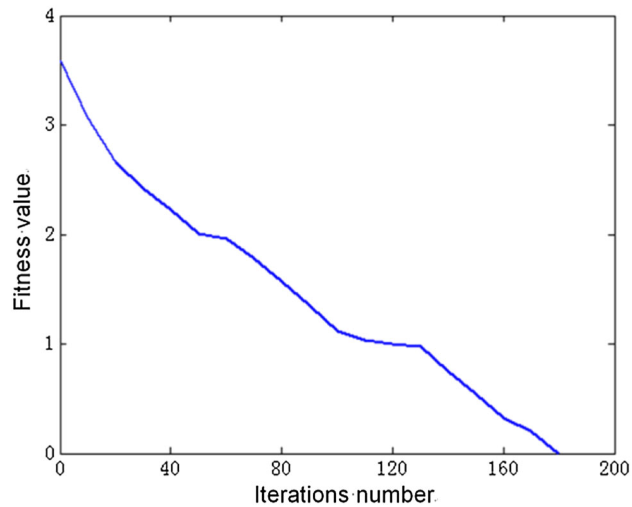

Fig. 1 Improved ant colony optimization algorithm for the LSSVM parameter optimization curve

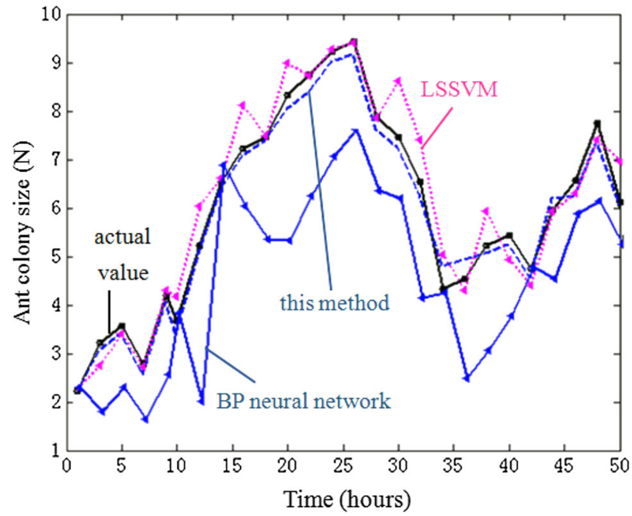

Fig. 2 Forecasting results of wind speed for three models

σ of the LSSVM algorithm by using 20th h wind speed data from MACO method is shown in Fig. 1.

5.3 Experimental results and analysis

Figure 2 shows the wind speed series forecast results of the proposed algorithm, the traditional LSSVM model and the BP neural network model. The conclusion compared with three models shows as follows. When the wind speed fluctuated wildly and varied inconsistently in the forecast time, BP neural network model cannot forecast the wind speed well and its forecasting result cannot keep up with the change of the actual wind speed. Therefore, there is a hysteresis phenomenon or a trend deviated from the actual wind speed leads to the undesirable forecast effect. Although the traditional LSSVM model can reflect the change trend of the actual wind speed basically and the forecasting ability of wind speed abrupt change point has been enhanced, there still is a certain amount of forecast error when the wind speed changes greatly. The LSSVM model with improved ant colony algorithm can forecast the trend of actual wind speed series better compared with the other two models. Naturally, the proposed model is consistent with the true value of the wind speed, and it can reduce the forecasting error of the traditional LSSVM model when the wind speed fluctuated wildly, so its stability and accuracy are improved.

Table 1 reveals the comparison of proposed method in this paper, traditional LSSVM model and BP neural network model. Table 1 show that the forecasting result by using BP neural network model is the worst of the three models, and the average relative error is reaching 18.85%. In contrast, the forecasting effect of LSSVM model is better than BP neural network model as the average relative error is 10.54%.

Table 1 Comparison on wind speed forecast error of three models

Forecast method	Mean square error / $(m\cdot s^{-1})$	Average absolute error / $(m\cdot s^{-1})$	Average relative error / (%)
This article method	1.6	0.46	6.65
LS-SVM	2.4	1.18	10.54
BP neural network	3.2	1.46	18.85

The forecasting effect of proposed method in this paper is the best in these three models since its average relative error is only 6.65%. The analysis mentioned above reveals that the forecast accuracy of optimized parameter LSSVM model improved by ant colony algorithm can be improved. The feasibility of this method and its advantages over the other two methods are reflected in this experiment.

6 Conclusion

At present, the forecasting problems of short-term wind speed are mainly solved by machine learning methods such as BP neural network, SVM and LSSVM. However, the SVM largely depends on the sample data. Especially the efficiency of solving the problem becomes lower with large number of samples. The application scope of BP neural network is limited as slow to learn and easy to fall into the local minimum problem. LSSVM method reduces the unknown parameters compared with SVM method, and reduces the complexity of the solution. On the other hand, the choice of parameters is extremely crucial when LSSVM is used to forecast the short-term wind speed. If the parameters are chosen improperly, it will often cause the model to owe learning or over learning, which directly affects the forecasting effect on wind speed. To solve this problem, a short-term wind speed forecast model with optimized parameter LSSVM model based on improved ant colony algorithm is presented in this paper. The simulation results show that the proposed algorithm is more accurate than the non-optimized LSSVM model and the BP neural network forecast model. Consequently, the proposed algorithm is more effective in short-term wind speed forecast. In the future, the parameters optimization method of LSSVM based on improved ant colony algorithm will continue to be used in other areas on predictive control.

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Yanan Li is a Ph.D. candidate. Her research area is Complex System Behavior and Modeling.

Peng Yang is a professor and Ph.D. adviser. His research area is Intelligent Artificial Limb, and Modern Advanced Manufacturing Equipment.

Huajun Wang is a professor. His research area is Wind Power Engineering and Motor Control.