Wind power short-term prediction based on SVM trained by improved FOA

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Abstract: The forecast accuracy of the wind power directly affects the operating cost of the network system, which is directly related to the supply and demand balance grid. Therefore, the forecast accuracy of wind power is very important. Considering the prediction accuracy not high, we propose an improved predictive method that is based on FOA-SVM. Since SVM penalty factor and kernel parameters having a great impact on the forecast Intensive, thus the improved FOA optimizes the parameters of support vector machine and train model with a good parameter optimization .Then the built model is used to the power prediction and evaluates the data finally. The prediction results show: the improved FOA-SVM can produce wind power prediction accuracy better.

Introduction

Due to the uncertainty of wind, randomness, wind power forecasting in large-scale wind farms and network operation plays a key role, in wind farms and network operation, we give an accurate prediction to the wind power .Not only dose it reduce the adverse effects of instability of wind on the grid effectively, but also it provide a strong basis to prepare in advance for power dispatching.

Currently, there are many methods which are applied into wind power forecasting, such as time series analysis [1], BP neural network [2], Kalman filtering method [3], wavelet decomposition [4] and etc. Time series analysis is a data processing method which uses model to analysis and process ordered random data that was observed. However, it will be very different for different models of order. Although BP neural network have good robustness, generalization, fault tolerance, but it is learning convergence slowly and easy to fall into local minimum global and can not get global optimum value. It is difficult for Kalman filtering method to get noise statistics. However, as the youngest of statistical learning theory, support vector machine can learn against small sample data. it also gets good generalization. Since the introduction of kernel function [5], it solves the curse of dimensionality problem effectively. Given the urgency of power prediction and the advantage of support vector machine in the sample regression, this paper established a support vector machine model to forecast short-term power.

Many studies have shown that kernel function parameter g and penalty factor c are main factors in support machine kernel which affect the prediction accuracy of SVM. So far, the selection of parameters has no law at all. The randomly selected parameter is less than ideal as demand accuracy. Therefore researchers use the advantages of other algorithms to optimize the parameter of SVM c,g.

The document [6] proposed a genetic algorithm to optimize the parameter of LS-SVM method and avoid shortage of parameters which is set by people, while reducing the optimization time. The document [7] proposed an optimization parameter based on ant colony algorithm to optimize parameters of SVM. The document [8] proposed support vector machine feature selection and parameter optimization based on bee algorithm. The document[9] proposed face recognition method based on immune algorithm which optimize parameter of SVM[10] and implement support vector machine parameter being automatically optimized and ultimately accurate classification of facial expression.

At present, Drosophila has not yet been used in wind power prediction which is a new algorithm proposed by Professor Pan Wenchao professor who is in Tai wan in 2011. In this paper, drosophila algorithm is simple, less arguments, less computation, high precision. So it is used to optimize parameter c,g of SVM. And this paper proposed improved optimization algorithm Drosophila which is applied into wind power prediction to improve accuracy.

Improves Drosophila Algorithm And Its Performance Analysis

Basic drosophila optimization algorithms

FOA is new method that deduces and seeks global optimization based on the foraging behavior of Drosophila which was proposed by Pan Wenchao who is in Taiwan in 2011. [11]

Its optimization step:

(1) initialize randomly Drosophila population position

Init X_axis

Init Y_axis //X and Y indicate the position coordinates of Fig. 1(x, y)

(2) Drosophila individual uses olfactory to search direction and distance of food

Xi=X_axis+Random Value//After random directions and distances and find goals' X coordinates

Yi=Y_axis+Random Value// After random directions and distances and find goals' Y coordinates

(3) Since we can not know the position of food, we firstly estimate the distance(Dist) between the position and the origin. Then we calculate the flavor concentration determination value (Si).

$$Disti = \sqrt{(x_i^{\ 2} + y_i^{\ 2})}; \qquad (1)$$

$$Si = 1/Disti \qquad (2)$$

(4) Flavor concentration determination value (s) is substituted into the flavor concentration determination function (or called Fitness function). Then we determined flavor concentration (Smelli) of the individual position Drosophila.

Smelli=Function(Si)

(5) Find the highest concentration fruit fly in the fruit flies.

[bestSmell bestIndex]=max (Smell)

(6) Retain the best flavor concentration and x, y coordinates, while Drosophila group flew to the determined position by the visual.

Smellbest=bestSmell

X_axis=X (bestIndex)

Y_axis=Y (bestIndex)

(7) Get into the iterative optimization, repeat steps 2-5, and determine whether the concentration of flavor taste better than the previous iteration concentration. If it is, we

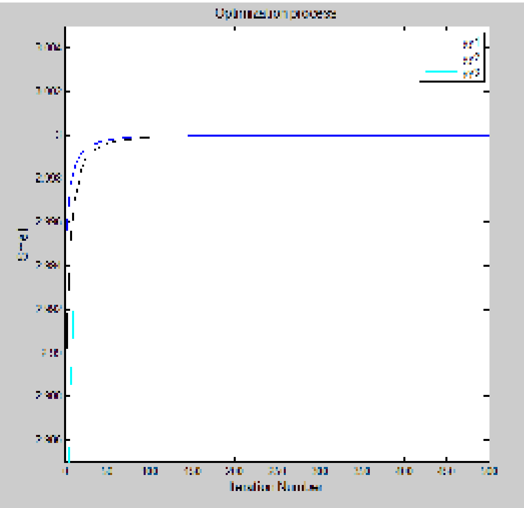
execute step (6), until we find the optimum flavor concentration.

Improved algorithm Drosophila

Considering the problem of parameters and premature, we change the population size, the initial poison setting and iteration step to improve Drosophila algorithm's search capability.

Population size is related to the level of search capability, the more flies in search of food, the faster you will find traces of food. Selecting the appropriate amount of the number of fruit fly and setting appropriate initial position can improve problem solving efficiency. While we select a different step value to affect the ability of searching.

Now we analyze the algorithm by solving extreme of function y = -5 + x ^ 2. we set the population 3,10,20 flies to search for respectively, and set the number of iterations 10 times, 100 times, 1000 times, and set iterative step value 2 * rand () - 1 , 20 * rand () – 10.



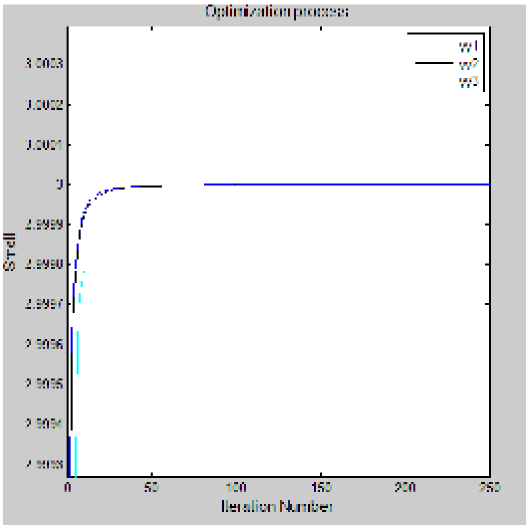


Fig.1 iterative step value is 2 * rand () – 1 **Fig.2** iterative step value is 20 * rand () – 10

As can be seen from the fig.1 and fig.2, it is different for the degree of convergence because of different populations, the number of iterations and iteration step.

Improve convergence of the drosophila

In the actual calculation, drosophila distance (Dist) gets the random value within a great range. So flavor concentration decision value (Si) may occur in a very small range and it is easy for FOA to fall into local optima and we can not find global extreme. Therefore we add a trip parameter (escape local optima) when we calculate flavor concentration determination value. We change the formula 2-3 by the parameter.

$$S_M = S_i + \Delta; \quad \Delta = Dist_i \times (0.5 - d); 0 \le d \le 1 \qquad (3)$$

In this way, the determination value Sm expand the distribution. When the Dist is very big, Sm avoid falling into the minimum.

Proof: assume H={h(1),h(2),h(3),….h(t),h(t+1)} the optimal value of each generation from the first generation to t + 1.So we satisfy

$$h(1) \le h(2) \le .... \le h(t) \le h(t+1) \qquad (4)$$

(1) When the flies search for food in a limited range, we can know the optimal solution must converge through the theorem that the number of columns must have the limit if it does not rise and has the lower bound.

(2) When the Dist get the random value in the great range, we adding the parameter Δ, Sm=Si+Δ will not fall into the local extreme value and will converge to the optimal solution.

SVM Model Based On Improved Drosophila Algorithm

Model Establishment

Firstly, we process and collect the data, select samples and test sets. Then we optimize parameters c,g by using fruit flies algorithm. Secondly, we build the model of prediction to test and analysis forecasting errors. It is shown in fig.3.

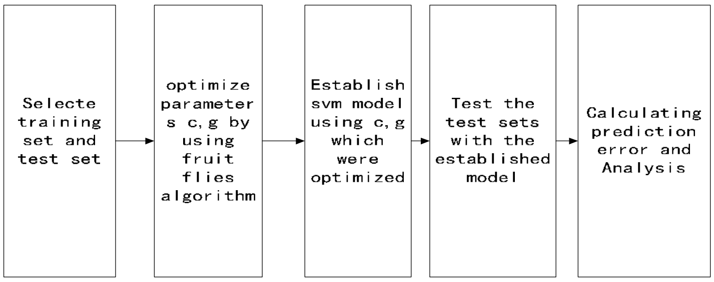


Fig.3 MFOA-SVM model

Choose the best parameter c,g using MFOA

Drosophila algorithm optimization goal is fitness function. Fitness function in this article is the rms error which is got after predicting data. Fitness value is smaller, the smaller the error. And the prediction rate of SVM regression is better. Specific steps are as follows:

First step: Determine the fitness function that we desired.

Second step: The population size and the number of iterations is initialized in the flies algorithm. Then we choose the SVM parameters.

Third step: We build SVM training model and predict the data, calculate the fitness function. Then we record the best parameter values in each generation group.

Four step: Update Drosophila group position, and repeate the second step until the maximum number of iterations is reached, then we output the optimal value.

Specific flow chart below fig.4:

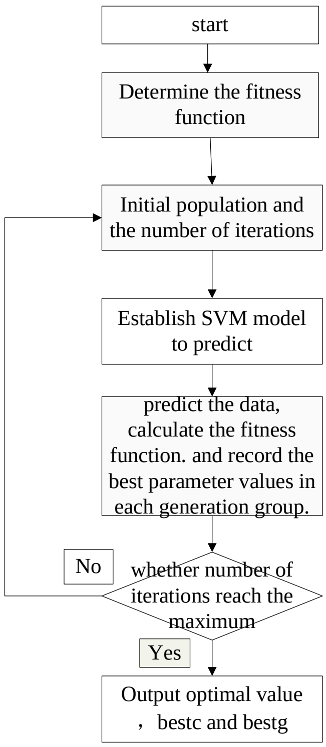


Fig.4 MFOA optimization flow chart

The Application Of MFOA-SVM In Wind Power Prediction

Wind power prediction plays an integral role in the overall wind farm. The accuracy of the prediction accuracy will have a direct impact on the supply and demand balance of the grid. And it has a decisive influence on the utilization of wind resource. Thereby increasing the prediction accuracy of power is very important to the entire wind farm. This paper predicts the data of wind farms based on svm power prediction model and optimize the parameters by using drosophila algorithm to improve prediction accuracy.

Data processing

In this paper, we put the wind farm owning GW82-1500 - km fan as the research object, using MATLAB2009 platform and support vector machine (SVM) toolkit toolbox Libsvm - mat to finish training and prediction of data samples. We use the data which is from the October 10 wind farm wind turbines run of measured data as an example to build sample set. The power value of the wind turbines is divided into training samples(Table1), training objectives(Table2), test samples(Table3) and test objectives(Table4) .We put the data that is in a mouth 20 days before as the training sample, the data of later 10 days as the test sample, interception 720 groups of data on October 2nd day to experience .Selected data is in the fan running stage, but will still be defective machine, fan for a long time for some downtime caused by data more missing time. We take out them directly. For less or no missing data, missing data are only changed data using the following methods to solve:

$$\text{If} \quad \begin{aligned} &|P(d,t)-P(d,t-1)|> \\ &\partial * P(d,t-1) \,\&\&\, |P(d,t)-P(d,t+1)| \\ &> \partial * P(d,t+1) \end{aligned} \qquad (5)$$

$$\text{Then} \quad P(d,t)=[P(d,t-1)+P(d,t+1)]/2 \qquad (6)$$

In the formula (4-2) ,P (d, t) is the power value of first t time ,d day, P (d, t - 1) is the value of first t - 1 time   d day values, P (d, t + 1) is the value of first t + 1times d day, said thresholds.

Table 1 Part of the training samples

	(kw)	(kw)	(kw)	(kw)	(kw)
0:00	710.0189	732.8741	441.9693	245.0219	577.892
1:00	732.8741	441.9693	245.0219	577.892	156.6927
2:00	441.9693	245.0219	577.892	156.6927	25.78428
3:00	245.0219	577.892	156.6927	25.78428	67.37646
4:00	577.892	156.6927	25.78428	67.37646	154.8993
5:00	156.6927	25.78428	67.37646	154.8993	389.0497
6:00	25.78428	67.37646	154.8993	389.0497	765.575
7:00	67.37646	154.8993	389.0497	765.575	892.1947
8:00	154.8993	389.0497	765.575	892.1947	950.681
9:00	389.0497	765.575	892.1947	950.681	999.2083
10:00	765.575	892.1947	950.681	999.2083	1163.499
11:00	892.1947	950.681	999.2083	1163.499	1158.947
12:00	950.681	999.2083	1163.499	1158.947	1033.062
13:00	999.2083	1163.499	1158.947	1033.062	1029.216
14:00	1163.499	1158.947	1033.062	1029.216	563.7418

Table 2 Part of the training samples

	(KM)	(KM)	(KM)	(KM)	(KM)
4:00	577.892	156.6927	25.78428	67.37646	154.8993
5:00	156.6927	25.78428	67.37646	154.8993	389.0497
6:00	25.78428	67.37646	154.8993	389.0497	765.575
7:00	67.37646	154.8993	389.0497	765.575	892.1947
8:00	154.8993	389.0497	765.575	892.1947	950.681
9:00	389.0497	765.575	892.1947	950.681	999.2083
10:00	765.575	892.1947	950.681	999.2083	1163.499
11:00	892.1947	950.681	999.2083	1163.499	1158.947
12:00	950.681	999.2083	1163.499	1158.947	1033.062
13:00	999.2083	1163.499	1158.947	1033.062	1029.216
14:00	1163.499	1158.947	1033.062	1029.216	563.7418
15:00	1158.947	1033.062	1029.216	563.7418	733.1421
16:00	1033.062	1029.216	563.7418	733.1421	1104.431
17:00	1029.216	563.7418	733.1421	1104.431	1455.435
18:00	563.7418	733.1421	1104.431	1455.435	1405.721
19:00	733.1421	1104.431	1455.435	1405.721	1421.187

Table 3 Part of the training samples

	(KW)	(KW)	(KW)	(KW)	(KW)
0:00	156.6927	25.78428	67.37646	154.8993	389.0497
1:00	765.575	892.1947	950.681	999.2083	1163.499
2:00	1158.947	1033.062	1029.216	563.7418	733.1421
3:00	1104.431	1455.435	1405.721	1421.187	1120.528
4:00	1050.017	1260.948	1297.926	1152.893	1393.266
5:00	1164.565	1036.927	1352.436	803.8626	800.4376
6:00	1053.818	1288.976	1331.232	1477.421	1517.728
7:00	1512.906	1161.186	594.5951	886.6741	1182.627
8:00	1230.506	1017.23	1413.532	1376.279	601.5649
9:00	13.63978	35.89524	90.80847	126.3859	114.4184
10:00	560.9813	235.7495	81.6828	58.63972	194.5166
11:00	78.88215	77.28573	13.52231	60.96592	138.2268
12:00	86.38577	72.04039	252.1552	566.2648	548.5013
13:00	757.1951	754.8292	786.1591	386.035	441.7472
14:00	722.0044	753.708	1425.062	1402.225	1467.582

Table 4 Part of the training samples

1399.412	1396.222	1408.518	1443.788	1351.051
1472.2	1407.683	800.6431	570.3044	131.2985

Experimental process

According to 3.1 figure 3 for model establishment and prediction, parameter selection shall be carried out in accordance with the flow chart of figure 4, choose RBF kernel function, the model of specific training steps are as follows:

(1) Eliminate, transform and add data collected
(2) classify data and the normalized processing
(3) initialize population size and the number of iterations and train the SVM model to determine the optimal parameter c, g
(4) We put the processed data into the SVM model to predict
(5) According to the fitness function of what we need, we calculate the fitness value of each generation and record the best value
(6) Through the comparison of each iteration, it is concluded that the optimal value. we output the prediction accuracy.

Results analysis of experiment

We divide data provided into training samples and testing samples, and put the data normalize processing. Through the FOA - training SVM model, get the kernel function parameters: the bestg = 0.1687, bestc = 3.3740, using the obtained parameters test and the normalized processing, the output data as shown in figure 5 and figure 6

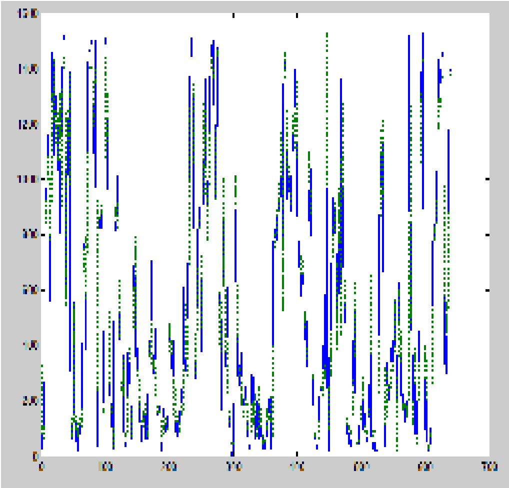
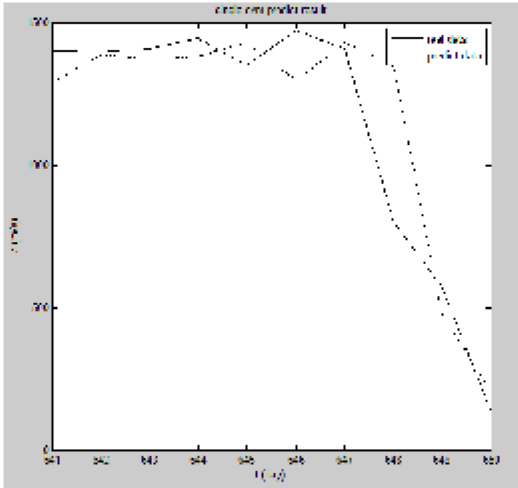
 

Fig.5 original data and optimized data of test sample **Fig.6** original data and optimized data of test goal

From figure 5 and figure 6 we can see through the improved MFOA - SVM optimization that prediction effect is remarkable by changing the population, the number of iterations and iteration step value, continuous experiment. Finally the average relative errors (in fig.7) can achieves 0.1429, compared to the error 0.1948 of not using MFOA optimization significantly increased, and the correlation is from 0.68 to 0.84. Thus prediction accuracy is improved.

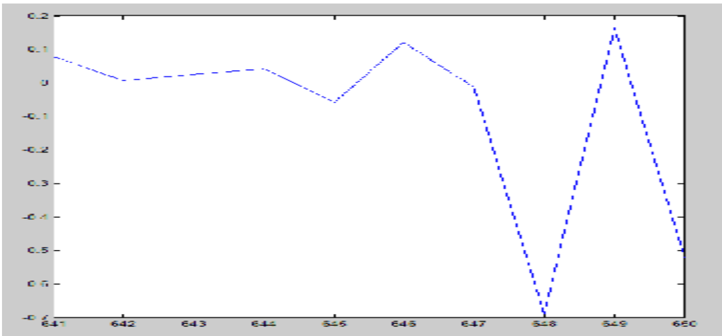


Fig.7 test target prediction after the average relative error

Conclusions

Wind power prediction is very important for the resources utilization. Accurate forecast is good for power system dispatching departments to adjust scheduling plan timely. Meanwhile, it can reduce the influence of instability of wind power grid. Based on the experimental analysis we adopt an improved algorithm of fruit flies to optimize the parameters of the SVM and build prediction model based on MFOA-SVM to improve the precision of prediction.The simulation results show that fruit flies as a relatively new optimization algorithm used in wind power prediction also shows a very good side.

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