Short-Term Load Forecasting of LSSVM Based on Improved PSO Algorithm

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Abstract. Based on the empirical, the precision of the forecasting will directly affect the reliability, economy and quality of power supply in power system. An improved particle swarm optimizer (IPSO) is proposed to be used on the least squares support vector machine (LSSVM) algorithm, which optimized the initialization parameters and improved the accuracy of short-term load forecasting. This thesis use the historical data of a certain grid to set up the short-term load forecasting model based on the optimization algorithm. While the data had comprehensive consideration the meteorology, weather, date, type and other factors which influencing the load. Compare with the LSSVM algorithm and the standard PSO-LSSVM, the empirical results show that IPSO-LSSVM model is more applicable in terms of convergence effect, accurate prediction and fast speed. The IPSO not only improves the accuracy of load forecasting, but also prevents LSSVM from great reliance on empirical results and random selection.

Keywords: load forecasting, improved particle swarm optimization, least square support vector machine, parameter selection.

1 Introduction

Load forecasting is important to power grid security, economic and high-quality operation. As is known to all, power system is a strong nonlinear system, load forecasting is very complex and need to consider many factors. In order to achieve a higher prediction precision and computational efficiency. The neural network prediction model and the fuzzy system forecasting model have been subjected to intensive studies, which has shown that the generalization ability of this kind of model is often lowly.

The support vector machine (SVM) model has been widely concerned in recent years[1]. This model has gotten the smaller actual risk based on the minimum structure risk principle. Meanwhile, minimize the empirical risk and VC dimension, then it has a better generalization ability for the new sample[2]. While the least squares support vector machine (LSSVM) is an extension of the standard SVM, it use a different loss function from the SVM. The LSSVM use equality constraints instead of inequality constraints so as to minimize square error. In the process of solving linear equations,

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the forecasting problem has been simplified and the forecasting efficiency has been obvious improved[3].

The LSSVM have been applied in a number of studies. Literature [4] has put forward a short-term load forecasting model based on the chaotic characteristic of load and LSSVM. Literature [5] has put forward the accounting method of LSSVM short-term load forecasting model, which is combined with rough set theory and genetic algorithm. Literature [6] has put forward a kind of intelligent combination power short-term load forecasting method, which is combined with the gray model and LSSVM regression algorithm. Literature [7] has proposed a method for electric power system short-term load forecasting, which has used the wavelet transform and LSSVM hybrid model. And literature [8] has applied the regression SVM method to power system short-term load forecasting. The above literatures have used LSSVM to overcome the disadvantages of neural network, such as over-fitting, slowly convergence speed, and easy to fall into local extremum, but the prediction accuracy is affected by the parameters. Although it has many advantages, but there is still a weakness need to be improved. That is the select of the parameters will affect the final accuracy. Although the method of determining the parameters has been discussed in the literatures, but these methods are basically based on cross check test heuristics or just by experience, they are certain blindness.

According to optimize the initialization parameters of LSSVM prediction model, a new optimization (IPSO) algorithm has been drawn out. This IPSO algorithm has a quick convergence speed and high robustness, so as to improve the accuracy of load forecasting. Research shows that the IPSO-LSSVM model has more applicable in terms of convergence effect, much more accurate prediction and faster training speed compared with the LSSVM algorithm and the standard PSO-LSSVM algorithm.

2 Improvement of the Standard PSO Algorithm

2.1 The Standard PSO Algorithm

The PSO algorithm is an arithmetic to obtain the optimal solution of particles through the iterative search, which the initial state of particles are random. In the process of iteration, the particles update themself by tracking two extreme value. One is the best solution of the particles themselves, known as the individual extremum p_{ibest}. Another is the optimal solution of entire population, know as the global extremum g_{best} [9-10]. In the standard PSO algorithm, the updating equations of particle's velocity and position are expressed as follows:

$$v_{id}^{t+1} = w^t v_{id}^t + c_1 r_1^t (p_{ibest}^t - x_{id}^t) + c_2 r_2^t (g_{ibest}^t - x_{id}^t) \tag{1}$$

$$x_{id}^{(t+1)} = x_{id}^{\ t} + v_{id}^{(t+1)} \tag{2}$$

Where

w is the coefficient of inertia weight, it is able to make the algorithm has the tendency to expand the search space and has the ability to explore new areas,

c_1 and c_2 are the accelerate constants, they represent the weight of accelerating statistical when each particle is pushed to the position of p_{ibest} and g_{best},

r_1 and r_2 are the random number between [0,1],

t is the number of iterations, mean the flight number of particle,

v_{id} is the flight speed of particle and x_{id} is the position of particle.

The standard PSO algorithm is easy to plunge into local extremum points, but the function have more than one local extremum point. The model would failure to get the correct results and resulting in premature convergence.

2.2 IPSO Algorithm

The IPSO algorithm use diversity metrics to describe the population distribution, thus guide the select of initial population on the basis of standard PSO algorithm, in order to avoid premature convergence.

This thesis has put forward the improvement method of PSO algorithm as follows:

(1) Average the particle distance of initial particle swarm

The selection of initial particle swarm is random. In order to increase the searching probability of the global optimal solution in ideal condition, its position should be throughout the whole space. Considering that the number of particle is limited, the solution space is opposite bigger. In order to ensure particles uniform distribution in the whole solution space and avoid local convergence, the concept of average particle distance has been introduced, which is defined as follows:

$$D(t) = \frac{1}{|m||L|} \sum_{i=1}^{|m|} \sqrt{\sum_{j=1}^{n} (p_{ij} - \overline{p_j})^2} \tag{3}$$

Where

m is the population size,

L is the maximum length of the diagonal in search space,

n is the dimension number of the search space,

p_{ij} is the coordinate value in the dimension j of particle i, and $\overline{p_j}$ is the average coordinate value in the dimension j of all particles.

The average particle distance means the discrete degree of particle distribution. It has improved the quality of the forecast and made particles can be searched in the whole search space.

(2) Judge whether premature convergence by fitness

The position of particle would determine its fitness value. And the state of population can be judged according to the overall change of the fitness value of particle. It reflects the aggregation degree of particle population.

Set the fitness value of the i[th] particle as f_i, and set the current population average fitness value as $\overline{f}$. Then, the variance of the population fitness value can be defined as follows:

$$\overline{f}=\frac{1}{m}\sum_{i=1}^{m} f_i \tag{4}$$

$$\delta^2=\sum_{i=1}^{m}\left(\frac{f_i-\overline{f}}{f}\right)^2 \tag{5}$$

Where
m is the particle number,
f is the normalized factor used to limit the size of δ^2.

The value of f has been determined by the following formula:

$$f=\begin{cases}\max\left|f_i-\overline{f}\right|, & \max\left|f_i-\overline{f}\right|>1\\ 1, & others\end{cases} \tag{6}$$

The δ^2, means the variance of fitness, reflect the concentration of particles in a population. With the increase of the number of iterations, the fitness value of particles in the population will be closer and closer, and the δ^2 will be smaller and smaller.

The improvement of the standard PSO algorithm can avoid the population fall into a local optimum and the phenomenon of premature convergence.

3 IPSO-LSSVM Forecasting Model

In this thesis, we select λ and δ with the IPSO algorithm. The regularization parameter λ and kernel function's kernel width δ need to be selected after determine the kernel function, when use LSSVM to solve the regression estimation problem.

3.1 The Establishment of the Model

The IPSO algorithm has been used to establishment the LSSVM model, the process is as follows:

(1)Input and process the historical data, form the training sample;
(2)Improve the set of PSO parameters;
(3)Initialize the particle swarm;
(4)Calculate the fitness value of particles, set p_{ibest} and g_{best};

(5)Calculate the average particle distance $D(t)$ and the fitness variance δ^2 in the current;

(6)If ξ is greater than the average particle distance $D(t)$ and β is greater than the fitness variance δ^2 (ξ and β is the threshold given in advance), deem there is a premature convergence, turn to (3), otherwise, turn to (5);

(7)Update each particle's current velocity and position according to the formula (1), (2), and form a new population of $X(t)$;

(8)Calculate each particle's fitness of new species $X(t)$, and compare to the individual extremum and global extremum, if better, replacement, otherwise, remain the same;

(9)Check whether the result meet the end of the optimization conditions (reach $T_{\max}$) or not, if meet, means the result has been reached the end of the optimization, it has already gotten the optimal solution, otherwise, let t=t+1, turn to (4);

(10)Transfer the optimal solution;

(11)To begin load forecasting.

The flow chart of short-term load forecasting based on IPSO-LSSVM model shown in figure 1.

3.2 The Setting of IPSO LSSVM Parameters

Set the search area of the IPSO algorithm for: $\lambda \in [0.1, 150]$, $\sigma \in [0.1, 10]$. The number of particles can be set up to 20. The distribution of the particle become wider and the scope of search space become bigger when the number of particle become larger, thus easier to find the global optimal solution, and the corresponding running time is longer at the same time.

The maximum number of iteration denoted by $T_{\max}$, which values for 10. And the coefficient of inertia weight denoted by w, it can be linear variation along with the iteration in the process of search, which usually scopes as[0.4,0.9].

Then considering c_1 and c_2. The particles would wander the local scope a lot when the accelerated constant c_1 becomes larger. While the oversize of c_2 would prompt particle premature convergence to local minimum. However, in the research of the short-term load forecasting of IPSO-LSSVM. If the value of c_1 and c_2 is too low, the particles would linger outside the target area before it was back. While the value is too high, the particles would suddenly rush to or over the target area. In order to balance the effect of random factors, c_1 and c_2 both values for 2. The average particle distance threshold denoted by ξ, and the fitness variance threshold denoted by β, respectively: ξ=0.001, β=0.01.

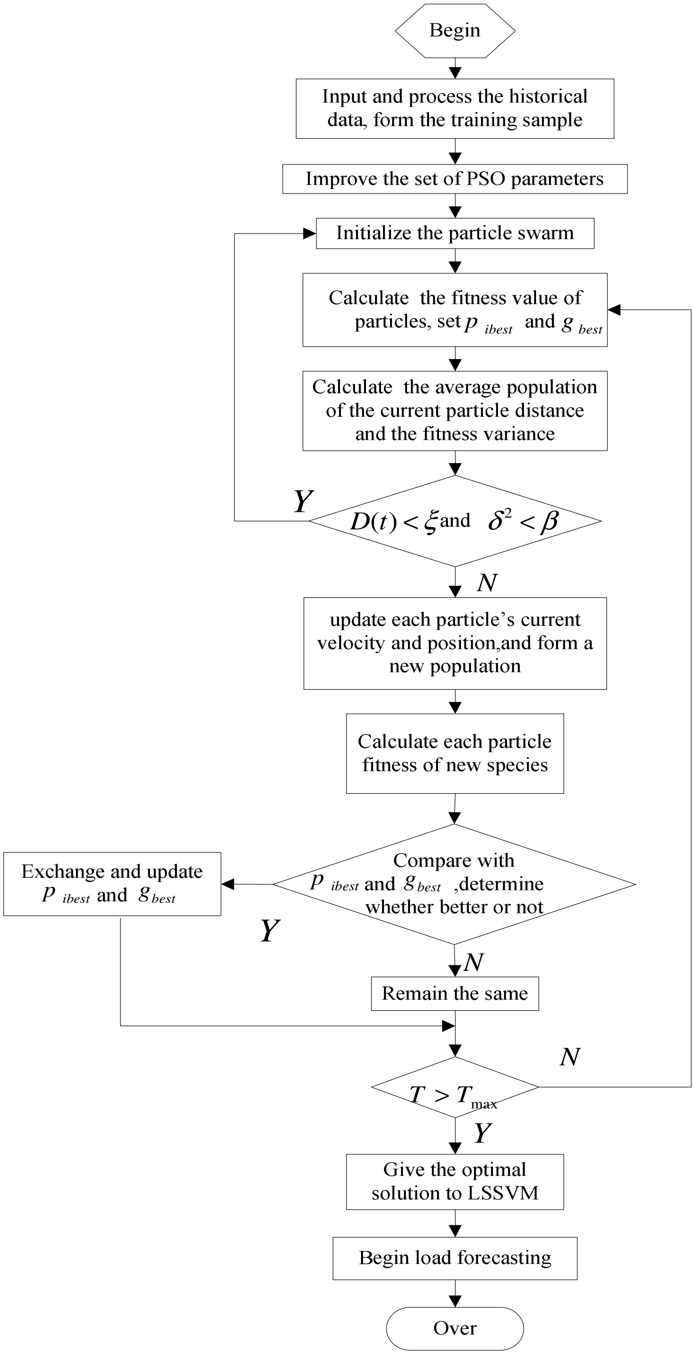

Fig. 1. Flow chart of short-term load forecasting based on IPSO-LSSVM model

4 Calculation and Analysis of Instance Modeling

This thesis has discussed the forecasting model combined with the actual data, in order to verify the effectiveness of the short-term load forecasting model. The data include the daily data and meteorological data of a regional power grid. These data were selected in March, 2009, it include the day type, day load, daily average temperature, daily maximum temperature, daily minimum temperature and daily average humidity.

This thesis select the historical load data as the alternative input variables to do the daily load forecasting. And the select of the historical load data is according to the following twelve characteristic parameters: the historical load, the humidity, day type value, the maximum temperature, the minimum temperature and average temperature in yesterday and two days ago at the same moment. The output of the model is the prediction of the load value.

This research do the modeling calculation and model test on the sample data, with the use of both standard PSO-LSSVM model and IPSO-LSSVM model. Predict and do forecast analysis with the historical data of the last week in march. Comparing with the actual value, the parameters optimization and load forecast errors of the two models have shown in table 1.

Table 1. The parameter optimization and load forecasting error of two models

Date	IPSO-LSSVM			standard PSO-LSSVM		
	λ	σ	ε %	λ	σ	ε %
March 25th	119.53	2.06	1.55	87.38	4.11	6.31
March 26th	57.00	8.99	1.72	94.72	2.32	2.03
March 27th	128.38	2.37	3.46	21.12	1.83	2.43
March 28th	111.74	2.37	2.52	111.76	2.37	2.96
March 29th	21.12	1.83	1.24	128.38	9.27	2.08
March 30th	94.72	2.32	1.39	57.00	8.99	1.68
March 31st	87.38	4.11	1.65	122.23	6.59	1.71

According to table 1, the prediction model based on IPSO-LSSVM has stronger optimal ability and search accuracy. Judging from the comparison results of the average relative error in the seven forecast days, the performance of the IPSO-LSSVM model is much better than the standard PSO-LSSVM model. Among them, the minimum relative error is 1.24%, the maximum relative error is 3.46%, the average relative error is 1.24%. And the average relative error of the standard PSO-LSSVM model is 19.2%.

The figures have shown that the IPSO-LSSVM model have better forecast precision. The experimental results also proved that the performance of the model will be greatly improved, while select an appropriate punishment parameter of kernel function parameters.

The fitting curve of the load forecasting results of two models during march 28th to march 30th in 2009 is shown in figure 2.

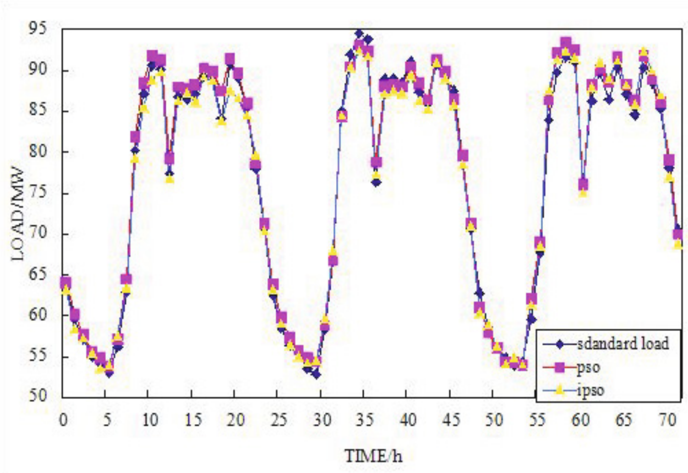

Fig. 2. The actual and forecast load curve

5 Conclusion

The LSSVM model could get the global optimal solution in theory, as for the algorithm transformed the problem which need to be solved into a convex quadratic programming problem. Also, it use the kernel function to solve the nonlinear problem, make the complexity of the algorithm do not affected by the dimension. Therefore the problem become much more simple and speed up the training of the model. According to the limited sample information, compromising between the complexity and learning ability of the model to ensure the better generalization ability.

The IPSO algorithm has selected the initial population and judged the premature convergence of the particles based on the information of species diversity. Essentially, it has introduced a process of rejection after the position of the particle update and attract each other. So as to reach the balance between particles' attraction and rejection, thus avoid the premature convergence. This algorithm update the particle's position when it has trapped in local optimum in the later search. Hence, lead particles jump out of local optimum.

This thesis has optimize selection the parameters of LSSVM through the IPSO algorithm. And it has been verified by experiment that the IPSO-LSSVM prediction model has better convergence effect, better prediction precision and faster training speed.

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