International Journal of Control and Automation
Vol.8, No.8 (2015), pp.181-188
http://dx.doi.org/10.14257/ijca.2015.8.8.19

Study on Short-Term Load Forecasting Method Based on the PSO and SVM model

Dao Jiang

School of Electronic and Information Engineering, Shunde Polytechnic, Shunde 528000 China
jiangdao1979@yeah.net

Abstract

The short-term load forecasting is an important method for security dispatching and economical operation in electric power system, and its prediction accuracy directly affects the operating reliability of the electric system. So the global optimization ability of particle swarm optimization (PSO) algorithm and classification prediction ability of support vector machine (SVM) are combined in order to realize the mutual supplement with each other's advantages in this paper. Firstly, the PSO algorithm is used to optimize the parameters of the SVM in order to obtain the optimal parameters of the SVM. Then a short-term load forecasting method based on combining the PSO and SVM according to the characteristics and influencing factors of short-term load forecasting is proposed. An actual power system in one region is applied to test and verify the short-term load forecasting method. The results show that the short-term load forecasting method takes on the good convergence and higher prediction precision.

Keywords: *Load Forecasting; Parameter Selection And Optimization; PSO; SVM; Electric Power System*

1. Introduction

Load forecasting [1] is to use a set of mathematical methods to deal with the pasted and future load in order to forecast the load value with meeting certain accuracy under some important conditions, such as the characters of system operation, added volume decision-making and the nature or society influence in the future. For the power transmission companies, the load forecasting is the basis of power programming, assuring the security, reliability, economy operation of electric power system. The power load forecasting is generally divided into the long-term, mid-term, short-term and exceed-short-term forecasting according to the time limitation [2]. The short-term load forecasting means that the unit is the month within one year, also refers to weeks, days, hours of load forecasting, it is mainly used for power system dispatching. The accurate short-term load forecasting results are helpful to make a proper plan of electric power volume, propose the appropriate running project and bidding strategy, and also promote the electricity plan management, section coal, fuel efficiency and reduce power generation cost, make the reasonable construction plan, improve the economic benefit and social benefit of electric power system[3-7]. Because the selection of some key parameters in the SVM directly affect the predicted results and the widespread of the forecasting model ,so it has not yet formed a unified model. Because it is a structured and general method to achieve the optimal selection parameters of SVM model. In the past time, we seek the optimal choice by using the experience, experiment contrast for finding extensiveness or using the provided cross test function with some soft-package. So this paper should mainly discuss the short-term load forecasting method based on particle swarm optimization algorithm and support vector machine in order to construct a optimal short-term forecasting model.

ISSN: 2005-4297 IJCA

2. Basic Method

2.1. Particle Swarm Optimization Algorithm

Particle swarm optimization (PSO) [8-10]was originally designed and developed by simulating the social behavior. The PSO is a population-based search algorithm. The PSO consists of many individuals, each individual has a position and a velocity. It works by attracting the particles to search space positions of the high fitness. In the PSO, each particle has a memory function and adjusts its trajectory according to the best visited position and the global best position in the population. The position of best fitness value visited by the swarm is called the global best (gb) and the position of best fitness value by individual is called the local best (pb). In a D-dimension space, each particle is treated as a point. The best previous position of the particle in the population is described as $x_i = (x_{i1}, x_{i2}, \cdots, x_{iD})^T$ .The velocity for particle i is represented as $v_i = (v_{i1}, v_{i2}, \cdots, v_{iD})^T$. The velocity and position are updated:

$$v_{ij}(t+1) = vw_{ij}(t) + c_1 r_1 \left(pb_{ij}(t) - x_{ij}(t)\right) + c_2 r_2 \left(gb_{ij}(t) - x_{ij}(t)\right) \quad (1)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (2)$$

$$w = w_{\max} - (w_{\max} - w_{\min}) \times I / I_{\max} \quad (3)$$

$v_{ij}(t+1)$ is the velocity of particle i at iterations j , $x_{ij}(t+1)$ is position of particle i at iterations j . w denotes the inertia weight coefficient of velocity, c_1 and c_2 denote acceleration coefficient. r_1 and r_2 are random numbers uniformly distributed in [0,1] which denote remembrance ability.

2.1. Particle Swarm Optimization Algorithm

Support vector machine (SVM)[11] is one of the most popular tools based on structural risk minimization in bioinformatics for a supervised machine learning methods. The basic characteristic of SVM is to map the original nonlinear data into a high-dimension feature space. The SVM is mainly used to solve the binary classification problem. The SVM is to find one division plane with meeting the given requirement in order to keep the point of the training set far away the plane. The SVM originated from the optimal classification surface from the linearly separable circumstance.

The Given the training sample is $\{x_i, y_i \mid i = 1,2,3,\cdots,m\}$, m is the number of samples, the set $\{x_i\} \in R_n$ represents the input vector, $y \in \{+1,-1\}$ indicates the corresponding desired output vector, the input data is mapped into the high dimensional feature space by using nonlinear mapping function $\phi(\bullet)$. Each sample point is satisfied:

$$y_i[w^* \phi(x_i) + b] - 1 \geq 0, i = 1,2,3,\cdots,m \quad (4)$$

where w represents the weight vector, b is the threshold value, At this time, the classification interval(Δ) is $2/w$. So the maximum interval is equivalent to the minimum of the $||w||^2$. The slack variables of the ξ_i and ξ_i are used to measure the distance between the actual value y_i and the support vector machine. The optimization problem of data separation plane is transformed into the following optimization problem:

$$\begin{cases} \min \frac{1}{2} \|w\|^2 + C\sum_{i=1}^{m} \xi_i \qquad i = 1,2,3,\cdots,m \\ s.t. \begin{cases} y_i(w^* x_i + b) \geq 1 - \xi_i \\ \xi_i \geq 0 \end{cases} \end{cases} \tag{5}$$

where C is penalty parameter.

3. The Optimized SVM Model Based On PSO Algorithm

3.1. The Selection of Kernel Function

The common kernel functions are: linear kernel function, polynomial kernel function, the radial basis kernel function, Sigmoid kernel function, Fourier kernel function and so on. For the regression estimating methods in different systems process data, there has the optimal kernel function with the best effect to corresponding. The radial basis function with the simple expression form, symmetric radial, good smoothness and analyticity has widely applied. So this paper chooses the radial basis function as the kernel function in the regression model, the specific form is as follows:

$$K(x, x_i) = \exp(-\|x - x_i\|^2 / \sigma^2) \tag{6}$$

where x is a m-dimensional input vector, x_i is the first i of the center in radial basis function and has the same dimension with x , σ is standardized parameter which determines the function about the width of the center ,and $\|x - x_i\|$ is the norm of the vector $x - x_i$, it means the distance between x and x_i .

The coefficient of kernel width σ reflects the correlation degree between support vectors, it associated with the input space range of learning samples. And the sample range of input space is bigger, the greater the σ value is obtained. If the σ is too small, the relationship between support vectors will flabby, the learning machine is relatively complex and the promotion ability can not be guaranteed .And if the σ value is too big, the influence between support vectors is too strong to achieve the sufficient accuracy by using the regression model.

3.2. The Determined Parameters of SVM Model

The SVM is used to solve regression estimation problem, we need to select the parameters (such as σ , C and ε) of the Gaussian radial function after we determine the kernel function. These parameters have a great influence to the performance of the learning machine, but up to now, there is no unified and effective theory guidance on how to select these parameters. For C and ε ,if the C is too small, the punishment for the data beyond ε in the samples is small, then make the training error larger; if C is too large, the corresponding punishment is too large, then the training error of the learning machine become smaller, and also the promotion ability becomes poor. If ε is too small, the requirements of the regression estimation precision is high, but the number of support vector increases; if ε is too large, the precision is reduced, the support vector quantity is little and the SVM sparsity is large. For LS-SVM, its necessary selection parameters of kernel function is σ and C, the less parameter selection makes the choose easier. In this article is using improved particle swarm optimization algorithm to select σ and C , the initialized parameters are as follows: the particle number m = 30, the maximum number of iterations $T_{\max}$ = 200, and the inertia weight coefficient can be change linear along with the iteration .The w in the process of search is [0.4, 0.9] and the accelerated constant is $c_1 = c_2 = 2$。

Particle swarm optimization algorithm has the advantages with simple structure, easy implementation, fast convergence speed and global searching ability, and it does not need to adjust too many parameters, so we regard that the particle swarm algorithm is used to select parameters of support vector machine (SVM) as a global search problem in the given space. A the optimized SVM model based on particle swarm optimization is proposed in this paper. The flow chart is shown in Figure 1.

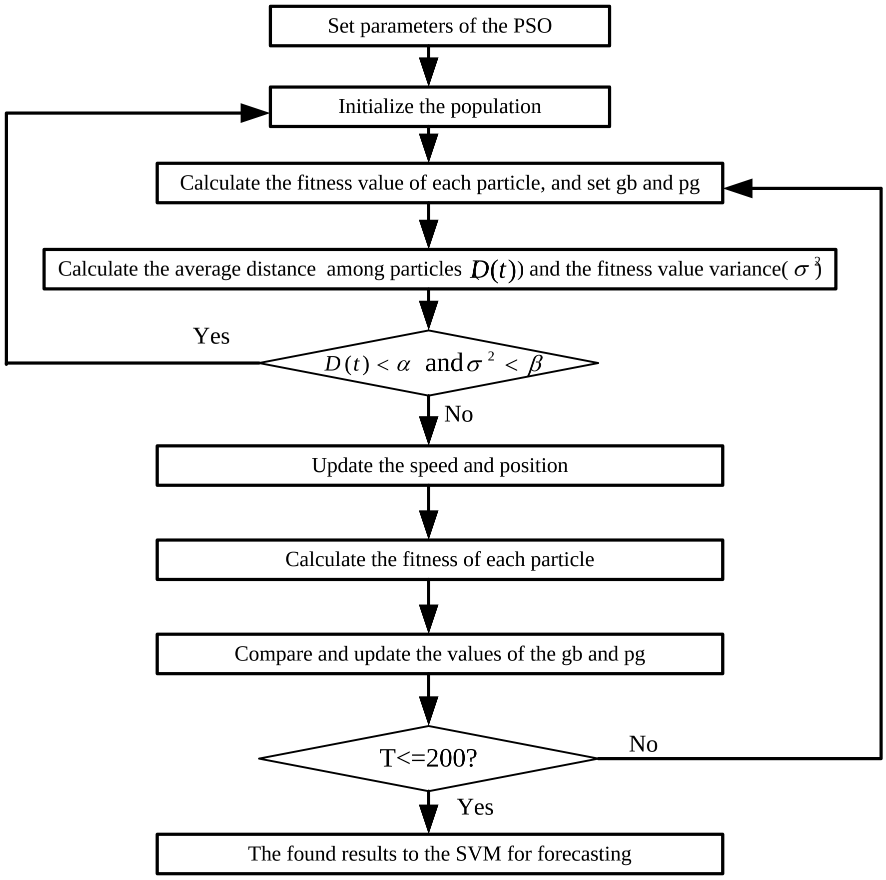


Figure 1. The Flow Chart of the Optimized SVM Model Based On The PSO Algorithm

The specific process of the improved PSO algorithm is: under ensuring the uniform distribution of initial population, the basic operation of the standard PSO algorithm is run in the first until the judgment particle falls into premature state. Then the solution space of particle is redistributed in order to quickly jump out the local optimal solution and speeds up the convergence.

The specific flow of the improved PSO algorithm is:

(1) Initialize the population according to the above mentioned method, the population size(m), the initial value of the inertia weight($w_{\max}$),the final value of inertia weight($w_{\min}$),the accelerated constant(c_1 and c_2), the maximum evolution value($T_{\max}$) or the terminated iterative threshold(ε) are set in here.

(2) Calculate and compare the fitness value of each particle ($f(x_i)$) according to the current position, the current position of the particle (i) is set to the optimal position p_{ibest} . The best particle is set to the optimal position g_{best} in the population.
(3) Calculate the average distance among particles ($D(t)$) and the fitness value variance (σ^2). If there are $D(t) < \alpha$ and $\sigma^2 < \beta$ (β and β are set to the given threshold in advance), and the precocity is determined, then turn to (4). Otherwise, turn to (5).
(4) Initialize the particle swarm once again according to the above mentioned method.
(5) Update the speed and position for all particles according the express (1) in order to generate new population ($X(t)$).
(6) Calculate the fitness of each particle. And the optimal history position is compared with the optimal history position of population. If the optimal history position is better, then the optimal history position of population is replaced by the optimal history position. Otherwise, remain unchanged.

4. The Short-Term Load Forecasting Method Based On PSO and SVM

The power system load changes take on the nondeterminacy. For example, the climate change and the accident occurrence and so on will cause a random interference for power load. On the other hand, the power load will regularly take place change according to the certain tendency under some certain condition. Consequently, when the short-term load forecasting of power system is studied, we will fully analyze, master and use the characteristics of the load changes. And the various influence factors also need be considered in here. So the load data in one region are regarded one example for analyzing. The load cycle and various influence factors of prediction are summarized, and these load characteristics are considered and used to build the short-term load forecasting model based on PSO and SVM for electric power system in order to improve the prediction precision.

The PSO algorithm is used to optimize the key parameters of the SVM model for forecasting. The obtained forecasting result is compared to the actual load data by using the error calculation method of average absolute value. In order to reduce the influence of accidental factors, the different samples in one region in 2009 are selected to respectively predict, then the predicted results are calculated in order to obtain the average value. The optimized values of parameters of SVM model are obtained by the iterative and calculation in table 1. The comparison of the load forecasting curve and the actual load curve are shown in figure 2.

Table 1. Forecasting Results By Using Some Samples (Standard PSO)

Date	Mar 20	Feb 26	Mar 28	May 16
C	0.1000	15.883	2.5933	150.00
Theta	1.7859	0.3241	9.3120	0.5576
Error%	1.1636	1.2713	1.6862	1.4237
		average error%	1.3872	

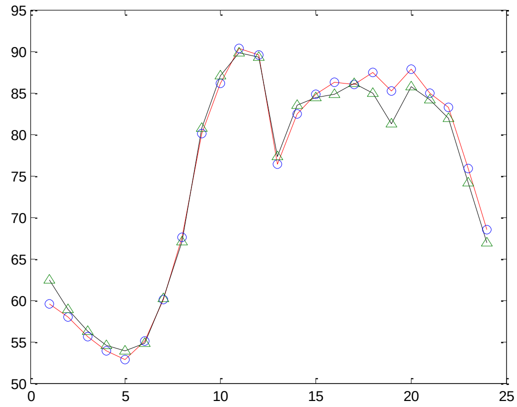


Figure 2. Comparison Result between the Load Forecasting Curve and Actual Load Curve

Figure 2 is to compare the fitting curve between the actual load curve and load forecasting curve by using of the established model by using two optimization methods. The band curve expresses the actual load curve and triangle curve expresses the forecasting load curve. It can be seen from Figure 2, the optimized SVM model by using PSO algorithm can obtain better prediction precision than SVM model. It can be also seen from Table 1 that the forecasting precisions are improved for each sample.

Table 2. Forecasting Results by Using Some Samples (improved PSO)

Date	Mar 20	Feb 26	Mar 28	May 16
C	0.1000	150.00	2.6252	110.68
Theta	0.7008	0.1731	8.5497	0.6176
Error(%)	1.1421	1.2132	1.6738	1.2153
	average error%		1.3192	

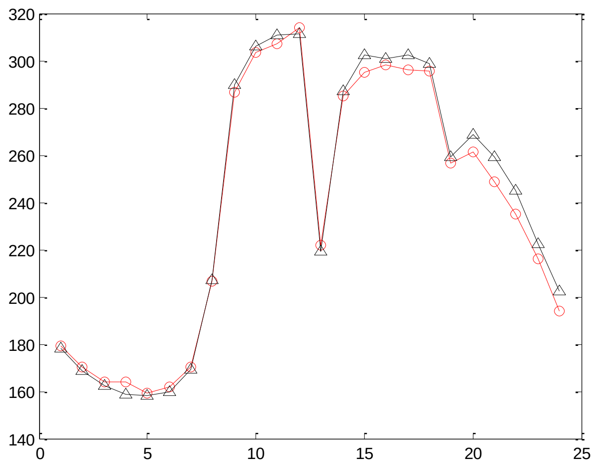


Figure 3. Comparison Result between the Load Forecasting Curve And The Actual Load Curve

The forecasting results are shown in Figure 3 and Table 2. The improved PSO algorithm takes on the stronger optimal ability and searching accuracy. In four forecasting days, the total average value of the absolute average error of the forecasting model is 2.06%, the maximum error is within 3.02%. As a result, the forecasting method based the improved PSO and SVM is effective and feasible for forecasting the short-term load.

5. Conclusion

The short-term load forecasting is an important daily work in the dispatching operations department of power system, it is the main basis of power generation planning and transmission scheme, and the short-term load forecasting has become one of the important contents of the modern power system management. This paper has integrated the latest research results in the field of short-term load forecasting, a new machine learning technique based on statistical learning theory - support vector machine (SVM) is introduced in detail. Through the comparison of traditional machine learning based on empirical risk minimization principle, it can be found that the SVM model has a more comprehensive and profound theoretical basis, and better solve practical problems, such as the small sample, nonlinear, high dimension and local minimum point and so on. In view of the traditional parameter selection method's defects that is mainly relies on the experience of trial and the low efficiency, PSO algorithm based on the parallel search strategy of population characteristics is used to iteratively search for the optimal parameter in order to automatically obtain the optimized parameters of SVM model. Meanwhile, in order to overcome the premature and convergence problem of standard PSO algorithm, the improved PSO algorithm based on population diversity is used to guide the selection of initial population and judge the particle premature and convergence phenomenon, in order to make the distributed particles in the solution space. When the particle evolution is easily trapped in local optimum, and guide the particles jump out of local optimal area by updating the location of the stagnation particles. It can keep the population activity, improve the ability of global optimization, effectively overcome the drawback of the PSO, and improve the overall performance of the PSO algorithm. A short-term load forecasting model based on the PSO algorithm and SVM is proposed for electric power system. Finally, the practical applications show that the short-term load forecasting method can obtain the ideal results.

Acknowledgements

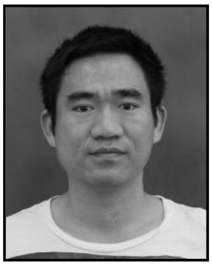
The authors would like to thank all the reviewers for their constructive comments. This research was supported by the Scientific and Technological Innovation Fund of Shunde District (No.20110302006). The program for the initialization, training, and simulation of the proposed algorithm in this article was written with the tool-box of MATLAB 2010b produced by the Math-Works, Inc.

References

[1] S. Tsuneyo, T. Itsuko and F. Yoshihiro.The load forecasting technology in the electric power distribution system.Electrical Engineering in Japan,153(2): 14-27. (2005)
[2] Y. Yan, A.M Yang.Fuzzy load forecasting of electric power system. Journal of Computers,7(8):1903-1910 (2012)
[3] A. Oonsivilai,M.E. El-Hawary. Wavelet neural network based short term load forecasting of electric power system commercial load. IEEE Canadian Conference onElectrical and Computer Engineering,3:1223-1228. (1999)
[4] A.K. Topalli, I. Erkmen. A hybrid learning for neural networks applied to short term load forecasting. Neurocomputing, 51(3):495-500. (2008)
[5] H.F. Shi, D.X Niu,Y.X Lu. The Short-Term Load Forecasting Model Based on Bayesian Neural Network. Power System Technology, 4: 118-124. (2012)

[6] D.X. Niu, B.G. Kou, Y.Y. Zhang, Z.H. Gu.A Short-term load forecasting model based on LS-SVM optimized by dynamic inertia weight particle swarm optimization Algorithm. Lecture Notes in Computer Science,5552: 242-250. (2009)
[7] H. Luis, B. Carlos, et al. Improved Short-term load forecasting based on two-stage predictions with artificial neural networks in a microgrid environment. Energies,6(9):4489-4507. (2013)
[8] Kennedy J, Eberhart R. Particle swarm optimization. Proceedings of the IEEE international conference on neural networks, IEEE Press, Piscataway,1942–1948.(1995).
[9] E Assareh, MA Behrang, MR Assari, A Ghanbarzadeh. Application of PSO (particle swarm optimization) and GA (genetic algorithm) techniques on demand estimation of oil in Iran. Energy. 35(12):5223-5229.(2010)
[10] Ch Sudheer, Nitin Anand, B.K. Panigrahi, Shashi Mathur. Streamflow forecasting by SVM with quantum behaved particle swarm optimization. Neurocomputing. 101:18-23 .(2013)
[11] Vapnik V. Statistical Learning Theory. New York: John Wiley & Sons, 253-256.(1998)

Author



Dao Jiang is a lecturer, received the Engineering Master degree in computer software from Jinan University in 2005, Guangzhou, China. The main research directions: Artificial Intelligence, Hybrid optimization algorithm.