Application of Support Vector Machine and Similar Day Method for Load Forecasting

Xunming Li[1], Changyin Sun[1,2,*], and Dengcai Gong[1]

[1] College of Electrical Engineering, Hohai University,
Nanjing 210098, China
[2] Department of Automation, Southeast University,
Nanjing 210096, China
*cysun@ieee.org

Abstract. Support Vector Machine (SVM) is a precise and fast method for the prediction of short-term electrical load and the similar day method is a simple and direct method for load forecasting. This paper tries to combine SVM model and similar day method for next day load forecasting. The proposed method forecasts the load of next day using SVM. Then, the load curve of a similar day is selected to correct the curve forecasted by SVM, which can avoid the appearance of large forecasting error effectively. Corresponding software was developed and used to forecast the next day load in a practical power system, and the final forecasting result is accurate and reliable.

1 Introduction

Load forecasting plays an important role in power system planning and operation. Basic operation functions such as unit commitment, economic dispatch, fuel scheduling and unit maintenance can be performed efficiently with an accurate forecast.

Research on short-term load forecasting has attracted wide attention for many years. Several major methods and techniques have been proposed and developed, including time series models, regression models, Box-Jenkins transfer function, expert system models, neural network models and fuzzy logic [1]. However, load forecasting is a difficult task as the load at a given hour depends not only on the load at the previous hour but also on the load at the same hour on the previous day, and on the load at the same hour on the day with the same denomination in the previous week. Generally, these methods are based on the relationship between load and factors influencing the load. However, the techniques employed for those models use a large number of complex and nonlinear relationships between the load and factors influencing the load. The traditional prediction methods are difficult to estimate these nonlinear relationships. Therefore, some new forecasting models have been recently introduced as expert systems, artificial neural networks (ANN), and fuzzy systems. Among these different techniques of load forecasting, application of ANN technology for electric load forecasting has received much attention in recently years. The main reason of ANN becoming so popular lies in its ability to learn complex and nonlinear relationships that are difficult to model with conventional techniques. However, there

L. Wang, K. Chen, and Y.S. Ong (Eds.): ICNC 2005, LNCS 3611, pp. 602 – 609, 2005.

are some disadvantages of ANN method such as network structure is hard to determine and training algorithm has the danger of getting stuck into local minima.

Recently, a novel type of learning machine, called support vector machine (SVM), has been receiving increasing attention in areas from its original application in pattern recognition to the extended application of regression estimation [2-3]. This is brought about by the remarkable characteristics of SVM, such as good generalization performance, the absence of local minima and sparse representation of solution. One key characteristic of SVM is that training SVM is equivalent to solving a linearly constrained quadratic programming problem so that the solution of SVM is always unique and globally optimal, unlike ANN' training which is time-consuming and requires nonlinear optimization with the danger of getting stuck into local minima. Recently, there is also a great deal of researches concentrating on applying regression SVM to short-term electrical load forecasting [4-6]. In short-term load forecasting, load of two days that have similar weather condition, same day class (workday or weekend) and several other similar factors are generally very close. From this view, the similar day method [7-8] has been developed. Flowing the idea obtained from the previous work [4], this paper tries to combine SVM theory and similar day method to forecast the next day electrical load. The proposed method uses SVM for next day electric load forecasting. The historical data of some previous days are used as samples data to train SVM. With the trained SVM, the load curve of next day is forecasted. At the same time, a similar day is selected by similar day method. Then, the correction should be done with the forecasted value by SVM when it violates the general rule of load curve of the similar day. This method is used to forecast the next day load of a practical power system in a week. The experimental result shows that the proposed method performs well on both the forecasting accuracy and the computing speed.

The paper is organized as follows. Section **2** gives a brief introduction to SVM in regression estimation and the similar day method. Section **3** presents the proposed method for load forecasting in detail. Section **4** discusses the experimental result and then several error evaluation indexes are engaged. Section **5** concludes the work.

2 The Regression SVM and Similar Day Method

2.1 SVM for Regression Estimation [3]

Given a set of data points $\{(X_i, y_i)\}_i^N$, ($X_i \in \mathrm{R}^n$, $y_i \in \mathrm{R}$, N is the total number of training sample) randomly and independently generated from an unknown function, SVM approximates the function using the following form:

$$f(X) = <\omega, \varphi(X)> + b \tag{1}$$

where $\varphi(X)$ represents the high-dimensional feature spaces which is nonlinearly mapped from the input space X. The coefficients ω and b are estimated by minimizing the regularized risk function (2):

$$\text{minimize } \frac{1}{2}\|\omega\|^2 + \text{C}\sum_{i=1}^{N}\left|y_i - <\omega, \varphi(X_i)> - b\right|_\varepsilon \tag{2}$$

$$\left|y_i - <\omega, \varphi(X_i)> - b\right|_\varepsilon =$$
$$\begin{cases} 0 & \left|y - <\omega, \varphi(X)> - b\right| < \varepsilon \\ \left|y - <\omega, \varphi(X)> - b\right| - \varepsilon & \left|y - <\omega, \varphi(X)> - b\right| \geq \varepsilon \end{cases} \tag{3}$$

The first term $\|\omega\|^2$ is called the regularized term. Minimizing $\|\omega\|^2$ will make a function as flat as possible, thus playing the role of controlling the function capacity. The second term $\sum_{i=1}^{N}\left|y_i - <\omega, \varphi(X_i)> - b\right|_\varepsilon$ is the empirical error measured by the ε-insensitive loss function (3). This loss function provides the advantage of using sparse data points to represent the designed function (1). C is referred to as the regularized constant. ε is called the tube size. They are both user-prescribed parameters and determined empirically.

To get the estimation of ω and b, (2) is transformed to the primal objective function (4) by introducing the positive slack variables $\xi_i^{(*)}$ ((*) denotes variables with and without *)

$$\text{minimize } \frac{1}{2}\|\omega\|^2 + \text{C}\sum_{i=1}^{N}(\xi_i + \xi_i^*)$$

subject to

$$\begin{aligned} & y_i - <\omega, \varphi(X_i)> - b \leq \varepsilon + \xi_i \\ & <\omega, \varphi(X_i)> + b - y_i \leq \varepsilon + \xi_i^* \\ & \xi_i^{(*)} \geq 0 \qquad\qquad i = 1, \ldots., N \end{aligned} \tag{4}$$

Final, by introducing Lagrange multiplier and exploiting the optimality constraints, the decision function (1) has the following explicit form:

$$f\ (X) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)K(X_i, X) + b \tag{5}$$

In function (5), $\alpha_i^{(*)}$ are the so-called Lagrange multipliers. They satisfy the equalities $\alpha_i \times \alpha_i^* = 0$, $\alpha_i \geq 0$, and $\alpha_i^* \geq 0$ where $i = 1 \ldots. N$, and they are obtained by maximizing the dual function of (4), which has the following form:

$$\begin{aligned} W(\alpha_i, \alpha_i^*) = & \sum_{i=1}^{N} y_i(\alpha_i - \alpha_i^*) - \varepsilon\sum_{i=1}^{N}(\alpha_i - \alpha_i^*) \\ & - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)K(X_i, X_j) \end{aligned} \tag{6}$$

Subject to

$$\sum_{i=1}^{N}(\alpha_i - \alpha_i^*) = 0. \qquad 0 \leq \alpha_i, \alpha_i^* \leq C. \quad i = 1 \ldots\ldots N$$

$K(X_i, X_j)$ is defined as the kernel function. The value of the kernel is equal to the inner product of two vectors X_i and X_j in the feature space $\varphi(X_i)$ and $\varphi(X_j)$, that is, $K(X_i, X_j) = <\varphi(X_i), \varphi(X_j)>$. The elegance of using the kernel function that one can deal with feature spaces of arbitrary dimensionality without having to compute the map $\varphi(X)$ explicitly. Any function that satisfies Mercer's condition can be used as the kernel function. Common examples of the kernel function are the polynomial kernel $K(X_i, X_j) = (<X_i, X_j> + 1)^d$ and the Gaussian kernel $K(X_i, X_j) = \exp(-(1/\sigma^2)(X_i - X_j)^2)$, where d and σ are the kernel parameters.

From the implementation point of view, training SVM is equivalent to solving the linearly constrained quadratic programming problem (6) with the number of variables twice as that of the number of training data points. The sequential minimal optimization (SMO) algorithm extended by Scholkopf and Smola is very effective in training SVM for solving the regression estimation problem. In this paper, an improved SMO algorithm [9] is adopted to train SVM.

2.2 The Similar Day Method [7]

In short-term load forecasting, load of two days are generally very close when they have similar weather condition, same day class (workday or weekend) and several other similar factors. Experiential forecaster can find out a similar day and correct the load curve of the similar day to forecast the load curve of the next day.

These central rules should be analyzed at first. In general, the changing of load between two days are influenced by following factors:

(1) Day types are different: loads in weekend are always lower than that in workday, and loads in Monday between midnight and morning are always lower than that in common workdays in that period of time.

(2) Weather conditions are different: weather conditions have a notable influence in electrical load, especially in summer and winter.

(3) Loads structure will change slowly along time. As to two days between a long period of time, even they have the same day type and weather conditions, the loads of two days also exist some differences.

From this view, the similar day method has been developed. The method is composed by two steps: the first is to select the similar day which has the minimal value of a difference estimation function; the second is to correct the load of the similar day according to the parameters of the forecasting day.

The mathematic model is presented in following:

$$\Delta P = P_{\mathrm{f}} - P_h = \phi(\alpha, \beta) \tag{7}$$

$$\|\alpha - \beta\| = \left[(\alpha_1 - \beta_1)^2 + (\alpha_2 - \beta_2)^2 + \cdots + (\alpha_k - \beta_k)^2\right]^{\frac{1}{2}} \tag{8}$$

there

ΔP − the variance of load between forecasting day and similar day,

P_{f} − load of forecasting day,

P_h – load of similar day,

$\alpha_1, \alpha_2, \cdots, \alpha_k$ – the values of factors which influence the load of a previous day,

$\beta_1, \beta_2, \cdots, \beta_k$ – the values of factors which influence the load of forecasting day.

The day with the minima of $\|\alpha - \beta\|$ would be selected as the similar day, and then the load of next day would be forecasted. The advantages of the method are simple, practical and comparatively precise.

3 The Proposed Forecasting Model

In a practical power system, the trend of electrical load can be described by linear changing model, periodic changing model and random model. According to linear changing model, A large part of load is so-called base load which would be not influenced by the change of weather, so in the proposed method, only the part which influenced by weather conditions evidently will be used as target inputs to train SVM. According to periodic model, the historical data in a certain previous period are selected as training samples. Then the SVM will be trained to describe the nonlinear relationship between influencing factors and electrical load.

The specific steps are presented in following:

First, transforming the non-numerical factors into numerical form. Taking sunlight for example**:** fine is set as 3, cloudy as 2,rain as 1. The maximal and minimal temperature can apply the actual values.

Second, treating disorder samples. Considering the proportion of the load in serial time, it is sure appearing disorder data when the change of load violates the general rule. Checking every point according to this principle to pick out all disorder data and correct them.

Third, for avoiding saturation problems, it is vital to scale input and target input to range of [0,1] as follows

$$X_{Normalization} = \frac{X_{actual} - X_{\min}}{1.5 * X_{\max} - X_{\min}} \tag{9}$$

There $X_{\max}$ and $X_{\min}$ are maximum and minimum values of training samples. This particular function selected for normalization is chosen based on some tries and errors.

Fourth, training SVM using the normalized samples. Then an effective algorithm SMO is employed there. Taking the influencing factors vector of forecasting day into the trained SVM, the 24 points load of next day will be forecasted.

Five, selecting similar day from previous days. The day with the minimal value of $\|\alpha - \beta\|$ is selected as similar day. The load curve of next day would be forecasted by correcting the load of similar day.

Finally, correcting the result forecasted by SVM. According to random model, the electrical load is influenced by a series of uncertain factors and it is hard to get a satisfy result absolutely using historical data. So, the similar day load curve is used to amend the result forecasted by SVM. When the change of forecasted load violates the regular pattern of result forecasted by similar day method, then this value is insecure usually, which should be corrected or instead by the load forecasted by similar day method. The correction can avoid the appearance of value with comparatively big error effectively.

4 Experimental Results

To evaluate the performance of the proposed load forecasting scheme, the SVM and similar day method were tested with data obtained from a sample study performed on the Henan Province Power System, to predict the daily energy consumption 24-hour ahead. The example data is historical load data in a practical electrical network in October and November in 2003. The data includes the data of weather conditions and the data of 24 points load in every day. The 24 SVM models are trained for 24-hour points. Using the forecasted weather information of next day, 24 load points of next day are forecasted. Our model adopts the improved SMO algorithm to train SVM and RBF kernel function $k(x,\tilde{x}) = \exp(-1/\delta^2 (x-\tilde{x})^2)$ is selected as the kernel function. Corresponding parameters are selected as follows $\delta = 1$, C = 0.1, $\varepsilon = 0.016$.

There are many error evaluation indexes to evaluate the result of daily load forecasting. In this paper, four relative error indexes are selected to evaluate the forecasting result of the proposed method. Table 1 represents the daily load forecasting errors from Nov.15 to Nov.21 in year 2003, and four error indexes of forecasting result are represented here.

Table 1. Relative errors of experimental result

Day	E_{MAPE} /%	E_{MSE} /%	$E_{\max}$ /%	$E_{\min}$ /%
Monday	1.73	2.06	1.66	1.06
Tuesday	1.98	2.35	1.62	4.07
Wednesday	1.67	2.11	0.38	1.34
Thursday	3.03	3.36	3.89	2.31
Friday	2.73	3.14	1.70	1.53
Saturday	2.15	2.39	1.69	3.85
Sunday	2.16	2.62	2.13	1.96

The content of table 1 indicates that the maximum of the mean average percentage error E_{MAPE} is 3.03% and the minimum is 1.67%. The forecasting result of this new method is accurate and reliable.

Fig. 1 is an example of daily load forecasting for Nov. 17,2003 forecasted by SVM solely. Fig. 2 shows the forecasting result corrected by similar day method. In fig.1, it could be observed that the values in point 9 and point 12 forecasted by SVM violated the general pattern of curve forecasted by similar day method. These values are insecure usually, and should be corrected or instead by the load forecasted by similar day method. There, an abnormal peak occurred in point 9 and the average of values in point 9 and point 11 is used to instead of it. The value in point 12 is lower than the value forecasted by similar day method with a large gap. So, that value is unbelievable and corresponding value in similar day method is used to instead of it. The corrected curve is showed in fig.2. The correction can avoid the appearance of values with comparatively large error, and the mean average percentage error of forecasting result is reduced from 2.23% to 1.73%.

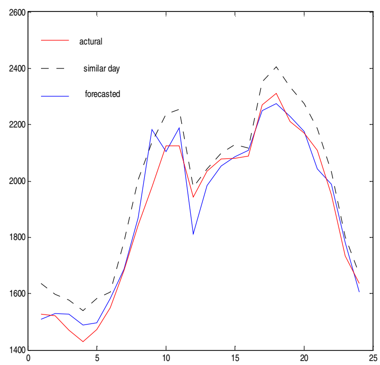

Fig. 1. The forecasting results of SVM

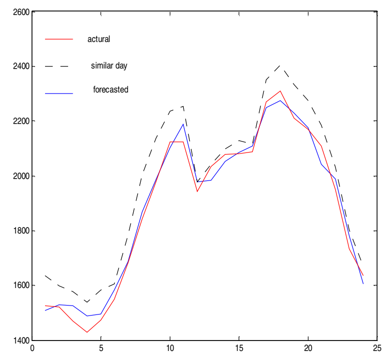

Fig. 2. The curve corrected by similar day method

5 Conclusion

This paper proposed a combined method for next day load forecasting based on SVM model and similar day method. The method used SVM to describe the nonlinear relationship between load and influencing factors, and corrected the forecasted results by the curve of a similar day to avoid the appearance of large forecasting error. This method behaves the advantages of both similar day method and SVM method, i.e. simple, practical, accurate and experience unreliable. Experimental result shows that this method is an effective method of high application value for next day load forecasting.

Acknowledgements

This work was supported by the National Natural Science Foundation of China under Grant 50595412, China Postdoctoral Science Foundation under Grant 2004036124, Jiangsu Planned Projects for Postdoctoral Research Funds and a start-up grant from Hohai University of China.

References

1. Hippert, H.S., Pefreira, C.E., Souza, R.C.: Neural network for short-term load forecasting: a review and evaluation. IEEE Trans. Power Systems, 16 (2001) 44-54
2. Vapnik, V.N., Golowich, S.E., Smola, A.J.: Support vector machine for function approximation, regression estimation and signal procession. Advance in Neural Information Procession System, 9 (1996) 281-287
3. Cao, L.J., Francis, E.H.: Support vector machine with adaptive parameters in financial time series forecasting. IEEE Trans. Neural Networks, 14 (2003) 1506-1518
4. Li, X.M., Gong, D., Li, L., Sun, C.Y.: Next day load forecasting using SVM. Lecture Notes in Computer Science, Springer, Berlin, 3498 (2005) 634-639
5. Yang, J.F, Cheng, H.Z.: Application of SVM to power system short term load forecasting. Electric Power Automation Equipment, 24 (2004) 30-32
6. Li, Y.C, Fang, T.J., Zhang, G.X.: Wavelet support vector machine for short-term load forecasting. Journal of university of science and technology of China, 33 (2003) 726-732
7. Cheng, S.: A new short-term load forecast method based on the similar day. Proceeding of Jiangsu Electrical Engineering Association, 18 (1999) 28-32
8. Ju, P., Jiang, W., Zhao, X.Y.: Ninety-six points short-term load forecasting—theory & applications. Automation of Electric Power Systems, 25 (2001) 32-36
9. Zhang, H.R., Han, Z.Z.: An improved sequential minimal optimization learning algorithm for regression support vector machine, Journal of Software, 14 (2003) 2006-2013