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Energy Procedia 16 (2012) 1455 – 1460

Energy Procedia

2012 International Conference on Future Energy, Environment, and Materials

Hybrid of ARIMA and SVMs for Short-Term Load Forecasting

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Abstract

Short-term load is a variable affected by many factors. It is difficult to forecast accurately with a single model. Taking advantage of the autoregressive integrated moving average (ARIMA) to forecast the linear basic part of load and of the support vector machines (SVMs) to forecast the non-linear sensitive part of load, a method based on hybrid model of ARIMA and SVMs is presented in this paper. It firstly uses ARIMA to forecast the daily load, and then uses SVMs, which is known for the great power to learn and generalize, to correct the deviation of former forecasting. Applying this hybrid model to a large sample prediction, the results show that it achieves the forecasting accuracy and has very good prospective in applications. So it can be used as a new load forecasting method.

Keywords-short-term load forecasting; ARIMA model; SVMs model; hybrid ARIMA-SVMs model

1. Introduction

The short-term load forecasting (STLF), an important part of Energy Management System (EMS), is the basis of power system dispatching automation, and plays a very important role in improving economy and security of system operating in power systems. With the development of power markets, STLF is becoming more and more important [1]. Load forecasting method can be divided into two categories: the traditional methods represented by time series and the modern intelligent methods represented by artificial neural network. The traditional methods are mainly time series analysis methods based on mathematical statistics including regression analysis method [2], Kalman filtering method [3], Box-Jenkins' autoregressive integrated moving average (ARIMA) method [4] and so on, and in which ARIMA is the most popular. The traditional methods have the advantages of mature technology and simple algorithm,

 doi:10.1016/j.egypro.2012.01.229

but these methods are based on linear analysis, as a result of which they are unable to forecast the nonlinear load series accurately. The modern intelligent methods are characterized by intelligent learning: including expert system [5], artificial neural networks (ANN) [6] and support vector machines (SVMs) [7-8], in which SVMs, owing to the great power to generalize, global optimal solution and fast calculation, have become the research hotspot of many subjects. In recent years, many combination forecasting methods that combine two or more models have been proposed, just as in paper [9] and [10].

STLF is to build a propriety mathematical model on the basis of historical load data and then forecast the load value of future days. The power load sequence not only has the tendency of appearing cyclically and increasing slowly, but also is known for its sensitivity affected by the weather and other factors, and randomness affected by emergency, so it is difficult to forecast accurately with a single model. For example, ARIMA model has advantage to forecast the linear basic part of load, but it can not forecast the non-linear sensitive part of load; ANN or SVMs model which both have good learnability can forecast the sensitive part, but they (especially the ANN) cannot accurately forecast the linear basic part of load because of focusing much on the nonlinear fitting and don't have excellent forecasting precision. For these reasons, to improve the prediction accuracy, a hybrid model of ARIMA and SVMs for STFL is presented in this paper. It firstly uses ARIMA to forecast the daily load, and then uses SVMs to correct the deviation of former forecasting, thus it can forecast not only the linear basic part of load, but also the sensitive part, and achieve the best effect.

The rest of the paper is organized as follows: Section II provides some basic theoretical aspects of ARIMA and SVMs, Section III describes how to use the hybrid ARIMA-SVMs model for STFL, carries out forecasting simulations and gives out the experimental results, and Section IV embraces the conclusions.

2. Hybrid ARIMA and SVMs Model

2.1 The ARIMA model

An ARIMA model actually uses autoregressive moving average (ARMA) model to fit stationary time series. Because the power load series are typically non-stationary time series, it must be transferred into stationary time series by difference transformation before using ARMA for modeling. This is what the word "integrated" means. The difference transformation can be divided into the order difference transformation and the periodic difference transformation. The first-order difference transformation is:

$$\nabla Y_t = Y_t - Y_{t-1} = (1-B)Y_t \tag{1}$$

Where, ∇ is the difference operator, Y_t and Y_{t-1} are the actual load values, B is the backward operator.

The periodic difference transformation is:

$$\nabla_s Y_t = Y_t - Y_{t-s} \tag{2}$$

Where, ∇_s is the periodic difference operator, s is the number of period.

With a couple of difference transformations (normally not more than three) above, the load series can be transferred into the stationary time series. And a method of judging whether the time series is stationary is: If the autocorrelation function (ACF) of it decreases approximately in exponential to zero, it is stationary. Otherwise, it is non-stationary and in need of difference transformation.

If the transferred series is stationary, we can use ARMA model to forecast. The ARMA model is formulated as follows:

$$\varphi(B)Y_t = \theta(B)e_t \tag{3}$$

Where, $\varphi(B)=1-\varphi_1 B-\cdots-\varphi_p B^p$, $\theta(B)=1-\theta_1 B-\cdots-\theta_q B^q$; $\varphi_i(i=1,2,\cdots,p)$ and $\theta_i(i=1,2,\cdots,q)$ are the model parameters; p and q are orders of the model.

Order determination (determining the value of p and q) and parameter estimation (determining the values of φ_i and θ_i) are the key steps of ARMA modeling. Currently the method of order determination is mainly the Akaike information criterion (AIC), and the methods of parameter estimation are mainly moment estimation, least-squares estimation, maximum likelihood estimation, etc. After having completed the order determination and parameter estimation, we can use the ARMA model to forecast the load.

2.2 The deviation correcting model of SVMs

For the learning of limited sample, the general algorithms (such as ANN) are based on empirical risk minimization principle, so they easily lead to "over-study" or low-generalization. The SVMs is designed to systematically optimize its structure based on the input training data, and can settle "small" sample problem well.

Given deviation data of training $\{(\boldsymbol{x}_i, y_i\}(i=1,2,\cdots,m)$, where each $\boldsymbol{x}_i \in R^n$ is the input vector with n-dimension, $y_i \in R$ is the associated desired output value of $\boldsymbol{x}_i$. Then the SVMs model is formulated as follows:

$$f(\boldsymbol{x})=\boldsymbol{w}\Phi(\boldsymbol{x})+b \tag{4}$$

Where $\Phi(\boldsymbol{x})$ is called the feature that is nonlinearly mapping from the input space $\boldsymbol{x}$. The $\boldsymbol{w}$ and b are coefficients that are estimated by minimizing the regularized risk function shown in formula (5).

$$\min_{\boldsymbol{w},b,\xi,\xi^*} \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + C\sum_{i=1}^{m} L_\varepsilon(y_i - f(\boldsymbol{x}_i), \boldsymbol{x}) \tag{5}$$

Where C is the regularized constant determining the trade-off between the empirical error and the regularization term. The larger the constant C is, the more the minimum experience risk is emphasized, and the lower the generalization of function f is. L_ε is linear loss function with ε -intensive zone, which is shown as follows:

$$\begin{aligned} L(y-f(\boldsymbol{x}),\boldsymbol{x}) &= |y-f(\boldsymbol{x})|_\varepsilon \\ &= \begin{cases} 0 & if \ |y-f(\boldsymbol{x})| \le \varepsilon \\ |y-f(\boldsymbol{x})|-\varepsilon & otherwise \end{cases} \end{aligned} \tag{6}$$

Using the Lagrange function and Wolfe's duality theory, and with the kernel function $k(\boldsymbol{x}_i, \boldsymbol{x}_j)$ introduced, the function given in (5) can be transformed into a quadratic programming problem as follows:

$$\begin{aligned} \min_{\alpha_i,\alpha_i^*} \quad & \frac{1}{2}\sum_{i,j=1}^{m}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)k(\boldsymbol{x}_i,\boldsymbol{x}_j) \\ & +\varepsilon\sum_{i=1}^{m}(\alpha_i+\alpha_i^*)-\sum_{i=1}^{m}y_i(\alpha_i-\alpha_i^*) \\ \text{s.t.} \quad & \sum_{i=1}^{m}(\alpha_i-\alpha_i^*)=0 \\ & 0 \le \alpha_i,\alpha_i^* \le C, i=1,2,\cdots,m \end{aligned} \tag{7}$$

Where α_i and α_i^* are Lagrange multipliers. They are obtained by solving this quadratic programming problem, and the input vector $\boldsymbol{x}_i$ corresponding the nonzero α_i, α_i^* is the support vector. Thus, the function (4) can be transformed into the following regression function:

$$f(\boldsymbol{x},\alpha_i,\alpha_i^*) = \sum_{i=1}^{m}(\alpha_i - \alpha_i^*)k(\boldsymbol{x}_i,\boldsymbol{x}_j) + b \qquad (8)$$

It is clear from (8) that the function f totally depends on the α_i and α_i^*. Finally, we can predict the deviation with regression function (8).

3. Simulation

In order to verify prediction performance of the hybrid ARIMA-SVMs model, we commit simulation with the model. The raw data, which comes from a certain electric power company in Heilongjiang of China, are used in the simulation. The data include the load, days of the week and weather data from March 1 to May 31, 1999. The method of using ARIMA to forecast the daily load is as follows. Firstly, the load series is transferred into the stationary time series by a periodic difference transformation and a first-order difference transformation. Secondly, the model of the raw load series is confirmed as ARIMA (3, 2, 6) through order determination, and the values of parameters are determined by parameter estimation. Finally, we use the confirmed ARIMA model to predict the 24 nodes load of the day immediately following two weeks. By repeating the method, the forecasting data and deviation data from March 15 to May 31 are obtained. By analyzing the deviation series, it is clear that the whole time series has obvious cyclical nature though the random fluctuation is constant in a short period of time. The reason for that is that ARIMA can't make use of the important external factors such as the weather, days of the week and so on. To improve the prediction accuracy, we use SVMs to extract the sensitive component from the deviation.

In order to correct the deviation, the SVMs with exponential kernel function are trained with the deviation sample, and the input sample is constructed based on the far-smallness near-bigness theory [11] and similarity theory [12]. The parameters of SVMs have a great effect on prediction accuracy, the proper values of them are determined by tests as follows: C=20, ε=0.17, σ=1. These values make SVMs have high generalization. Thus, the 24 nodes load deviations of the next day are predicted by 24 distributed SVMs, and we in turn predict a total of 1200 load deviations from April 12 to May 31. The result of forecasting load deviation is showed in Fig. 1. From the figure we can see that SVMs can very well extract the sensitive component from the deviation though the prediction isn't very accurate.

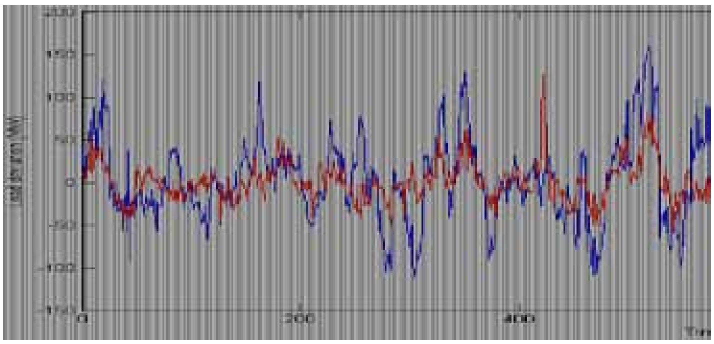

Figure 1. The curves of actual load deviation and the forecasting load deviation with SVMs

Adding the forecasting load deviation to the forecasting load, we have obtained the final forecasting load from April 12 to May 31 with the hybrid model. As a contrast, the individual ARIMA model and individual SVMs model are applied to forecast the same sample respectively. The forecasting results by different models are shown in the Fig. 2. Because the sample is too large, the figure just showed the forecasting loads from April 12 to April 18. We can see from the figure that the three models all achieved high precision, but the hybrid model predicts more accurately than the ARIMA model does.

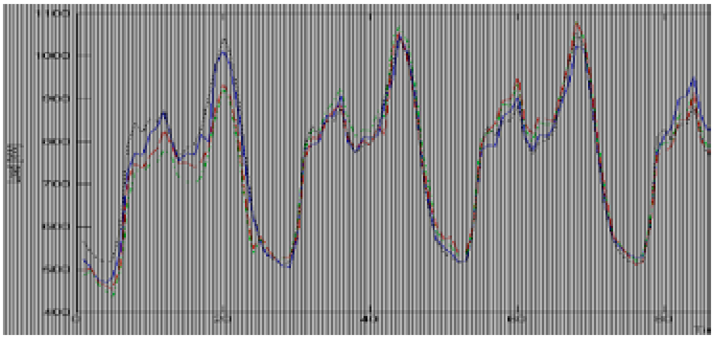

Figure 2. The curves of actual load and the forecasted load

Here, mean absolute percentage error (MAPE) and Root mean square error (RMSE) performance index are introduced to appraise and compare the different simulation results,

$$\mathrm{MAPE}=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_{(i)}-F_{(i)}}{Y_{(i)}}\right|\times 100\% \tag{9}$$

$$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_{(i)}-F_{(i)})^2} \tag{10}$$

Where $Y_{(i)}$ and $F_{(i)}$ are the values of the actual load and the forecasted load respectively, n is sample number and here is 1200. The comparison of forecasting results by different models is seen in the Tab. 1.

From the Tab. 1, we can see that ARIMA model achieved high precision, but the ARIMA-SVMs model can further raise the accuracy of simulation, i.e. the MAPE has declined by 0.65 percent, and the RMSE has declined by 7.77 MW. Its overall forecasting capability is improved. The results also show that this hybrid model is used to predict better than SVMs model. So the hybrid ARIMA-SVMs model has successfully realized the mutual supplement with each other in terms of advantages of ARIMA and SVMs.

Table 1 Comparison of forecasting results by the three models

Error analysis	ARIMA	SVMs	ARIMA-SVMs
MAPE	4.50%	4.00%	3.85%
RMSE(MW)	43.49	38.77	35.72

4. Conclusions

(1) As one of the most popular forecasting methods, ARIMA model can not make use of the important external factors such as the weather, days of the week and so on, so its forecasting deviation contains sensitive component which can be extracted for improving the prediction accuracy.

(2) Owing to the great power to generalize, global optimal solution and fast calculation, SVMs shows excellent performance in extracting the sensitive component, and can be used to achieve the purpose of correcting the deviation.

(3) The hybrid ARIMA-SVMs model has successfully realized the mutual supplement with each other in terms of advantages of ARIMA and SVMs. Through the simulation of large sample data, the results show that this hybrid model is much better than the two separate models of themselves.

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