# Short-term Load forecasting by a new hybrid model

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***Abstract*--Accurate short-term load forecasting (STLF) plays a vital role in power systems because it is the essential part of power system planning and operation. Considering that an individual forecasting model usually cannot work very well for STLF, a hybrid model based on the seasonal ARIMA model and BP neural network is presented in this paper to improve the forecasting accuracy. Firstly the seasonal ARIMA model is adopted to forecast the electric load demand day ahead, then by using the residual load demand series obtained in this forecasting process as the original series, the follow-up residual series is forecasted by BP neural network, finally by summing up the forecasted residual series and the forecasted load demand series got by seasonal ARIMA model, the final load demand forecasting series is obtained. Case studies show that the new strategy is quite useful to improve the accuracy of STLF.**

***Keyword: short-term load forecasting; ARIMA; BP; hybrid model***

## I. INTRODUCTION

Load forecasting has always been an essential and important topic for power systems, especially the STLF [1]. Basic operation functions such as unit commitment, economic dispatch, fuel scheduling, and unit maintenance can be performed more efficiently with an accurate forecasting [2]. However, load forecasting is a difficult task as the load at a given hour is dependent 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. So how to improve the forecasting accuracy is still a difficult and critical problem.

During the past years, a wide variety of techniques have been developed for STLF to improve the forecasting accuracy. Seasonal ARIMA model is frequently employed to forecast data with seasonal item. For instance, Choi et al. [3] used a hybrid SARIMA wavelet transform method for sales forecasting. Chen and Wang [4] developed a hybrid SARIMsA and support vector machines in forecasting the production values of the machinery industry in Taiwan. Considering that the load demand series always contain seasonal item, so the seasonal ARIMA model is adopted in this paper.

The BP neural network model is applied to a wide field of forecasting. Such as, Ke et al. [5] used the genetic algorithm-BP neural network to forecast the electricity power industry loan. Li and Chen [6] utilized the BP neural network algorithm to study the sustainable development evaluation of highway construction project. For the BP neural network can approximate the underlying function of the curves to any arbitrary degree of accuracy, therefore, this model is also employed to constitute the hybrid model of this paper.

The remainder of this paper is organized as follows. In section 3, seasonal ARIMA model and BP neural network are presented. In section 4, a case study of forecasting electricity load of South Australia (SA) State of Australia is demonstrated. Section 5 concludes this paper.

 

## II. THE HYBRID MODEL

### A. Review of the Seasonal ARIMA Model

Seasonal ARIMA is an extension of autoregressive integrated moving average (ARIMA).Only in sequence which circumstances are stable, ARMA model is effective, but SARIMA and ARIMA don't have such restrictions. Generally speaking, it is assumed that the time series $\{x_t | t = 1, 2, ..., k\}$ has mean zero. A non-seasonal ARIMA model of order $(p, d, q)$ (denoted by ARIMA $(p, d, q)$) representing the time series can be expressed as:

$$\begin{aligned} x_t &= \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + ... \\ &+ \varphi_p x_{t-p} + \varepsilon_1 - \theta_1 \varepsilon_{t-1} - \\ &\theta_2 \varepsilon_{t-2} - ... - \theta_q \varepsilon_{t-q} \end{aligned} \quad (1)$$

$$\varphi(B)\nabla^d x_t = \theta(B)\varepsilon_t \quad (2)$$

Where $x_t$ and $\varepsilon_t$ are the actual value and random error at time $t$, respectively; $\varphi_t$ and $\theta_t$ are the coefficients, $p$ is the order of autoregressive, $q$ is the order of moving average polynomials, $B$ denotes the backward shift operator, $\nabla^d = (1-B)^d$, $d$ is the order of regular differences, Random errors, $\varepsilon_t$ are assumed to be independently and identically distributed with a mean of zero and a constant variance of $\sigma^2$, and the roots of $\varphi(x) = 0$ and $\theta(x) = 0$ all lie outside the unit circle[7].

### B. Brief Introduction to the Back Propagation (BP) Neural Network

There are three layers contained in BP: input layer, hidden layer, and output layer. Two nodes of each adjacent layer are directly connected, which is called a link. Each link has a weighted value presenting the relational degree between two nodes. Assume that there are $n$ input neurons, $m$ hidden neurons, and one output neuron, the relationship between the output $(y_t)$ and the inputs $(y_{t-1}, y_{t-2}, ..., y_{t-n})$ have the following mathematical representation:

$$y_t = \alpha_0 + \sum_{j=1}^{m} \alpha_j g \left( \beta_{0j} + \sum_{i=1}^{n} \beta_{ij} y_{t-i} \right) + \varepsilon_t \quad (3)$$

We can infer a training process described by the following equations to update these weighted values, which can be divided into two steps:

- Hidden layer stage: The outputs of all neurons in the hidden layer are calculated by the following steps:

$$\text{net}_j = \sum_{i=0}^{n} v_{ij} x_i, \; j = 1, 2, \ldots, m, \quad (4)$$

$$y_j = f_H(\text{net}_j), \quad j = 1, 2, \ldots, m. \quad (5)$$

Here $net_j$ is the activation value of the $j$th node, $y_j$ is the output of the hidden layer, and $f_H$ is called the activation function of a node, usually a sigmoid function as follow:

$$f_H(x) = \frac{1}{1 + \exp(-x)}. \quad (6)$$

- Output stage: The outputs of all neurons in the output layer are given as follows:

$$O = f_o\left(\sum_{j=0}^{m} \omega_{jk} y_j\right). \quad (7)$$

Here $f_o$ is the activation function, usually a line function. All weights are assigned with random values initially, and are modified by the delta rule according to the learning samples traditionally [8].

## III. SIMULATION RESULTS

The electric load demand data used for the simulation are sampled from South Australia (SA) State of Australia at half an hour rate, so for one day, 48 load demand data are included. Fig.1 provides the load demand of SA from June 2, 2007 to July 14, 2007.

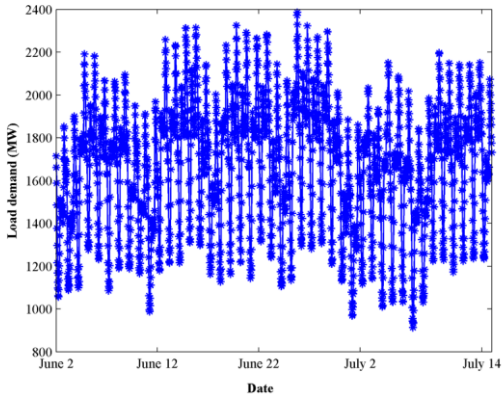


Figure 1. Electric load demand data

From Fig.1, it can be found that there exists significant similarity in load demand on the same day of each week, in other words seasonal components exist in load demand on the same day of each week. So the seasonal ARIMA model will be great helpful to forecast the load demand day ahead using the historical load demand on the same day several weeks ago. Using the data on June 2, June 9 and June 16 of 2007, the electric load demand on June 23 is forecasted. Then the same way, i.e., using the load demand data on the same day of the three sequential weeks to forecast the load demand on the same day of the adjacent week is adopted to forecast the load demand on June 30, July 7and July 14. Before the forecasting, value of parameters should be estimated, obviously, $s = 48$, values of parameters in forecasting load demand on June 23, June 30,July 7 and July 14 are listed in Table 1. By applying the estimated parameters shown in Table 1 to load demand forecasting, load demand results on June 23, June 30, July 7 and July 14 can be obtained by the seasonal ARIMA models. The forecasted load demand results are shown in Fig.2.

TABLE I. PARAMETERS IN SEASONAL ARIMA

| Parameters | Forecasting load demand on June 23 | Forecasting load demand on June 30 | Forecasting load demand on July 7 | Forecasting load demand on July 14 |
|---|---|---|---|---|
| $p$ | 1 | 2 | 1 | 1 |
| $d$ | 1 | 1 | 1 | 1 |
| $q$ | 1 | 1 | 2 | 1 |
| $P$ | 0 | 1 | 0 | 1 |
| $D$ | 1 | 1 | 1 | 1 |
| $Q$ | 1 | 1 | 0 | 1 |

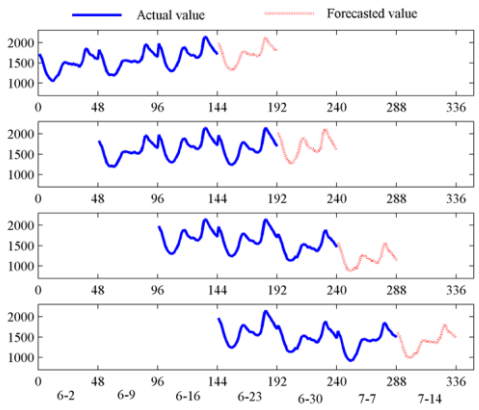


Figure 2. Forecasted load demand values by seasonal ARIMA models.

Using these forecasted load demand values, residual errors of load demand series on June 23, June 30 and July 7 will be obtained，as presented in Fig.3 Regarding the residual series as the original data series, then we use BP neural network to forecast the residual error series on July 14. In the constructing of the BP neural network, one of the most important tasks is training. When for training, the number of nodes in input layer is set as 2, which represent the load demand residual data on June 23 and June 30 at time $t$, and the corresponding 1-element output will be the residual data on July 7 at the same time, so there are total 48 samples for training. Except for determining the number of nodes in the input layer and output layer, the number of neurons in the hidden layer should also be given to construct the network. The number of neurons in the hidden layer we will adopt Hecht- Nelson's method [9], which is determined as follows: $h = 2*i+1$（8）Where $i$ is the number of inputs.

So the node number in the hidden layer is 5. The structure of the BP neural network is shown in Fig.4

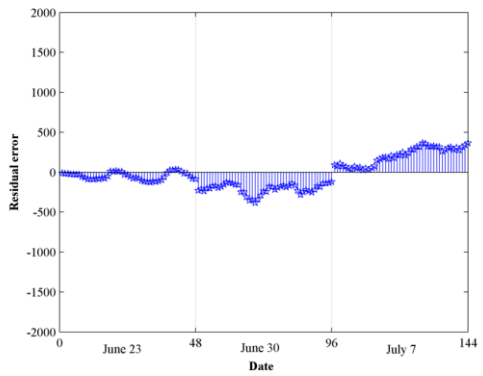


Figure 3. Residual error of the load demand forecasted by the seasonal ARIMA models.

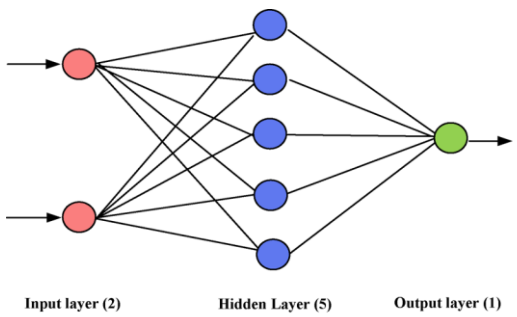


Figure 4. The architecture of the BP Neural network.

Then the forecasting can be implemented by the trained network. When for forecasting, the residual load demand data on June 30 and July 7 at time $t$ are used for inputs, with which the same time's load demand on July 14 can be forecasted. Forecasting results are plotted in Fig. 5.

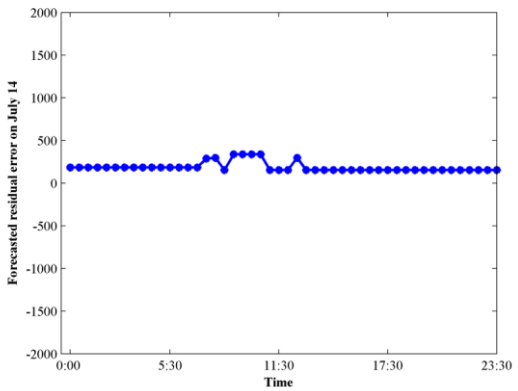


Figure 5. Residual error on July 14 forecasted by the BP neural network.

Finally, by summing up this forecasted residual series to the forecasted load demand obtained by seasonal ARIMA model, the final load demand can be got, which is shown in Fig.6.

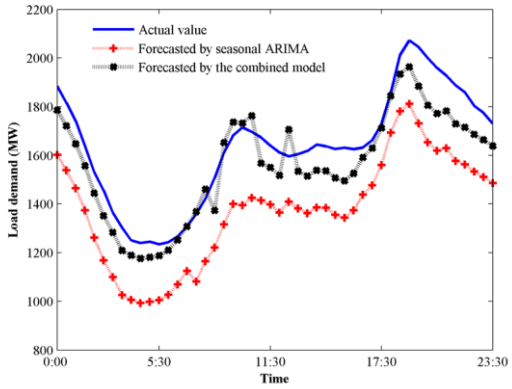


Figure 6. Actual and forecasted load demand values.

In order to evaluate the performance of the new forecasting strategy, two error measure criteria, i.e., the root mean square error (RMSE) and the mean absolute percentage error (MAPE) are used, the forecasting effect is better when the loss function value is smaller; the two error measure criteria are expressed as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \hat{x}_i\right)^2} \qquad (9)$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \times 100\% \qquad (10)$$

Where $x_i$ and $\hat{x}_i$ represent the actual and the forecasted load demand at time $i$, and the value of $N$ in our simulation is 48. Values of RMSE and MAPE obtained by individual seasonal ARIMA model and by the hybrid model based on seasonal ARIMA and BP neural network are listed in Table 2.

TABLE II. COMPARISON OF RMSE AND MAPE

| Models | RMSE | MAPE |
|---|---|---|
| Individual | 260.7365 | 15.97 |
| Combined | 97.1355 | 5.12 |

From Table 2, it can be seen that the value of RMSE varies from 260.7365 in the individual seasonal ARIMA model to 97.1355 in the combined model, while MAPE is reduced from 15.97% to 5.12%. Therefore, the combined model improves the load forecasting accuracy as compared to the individual seasonal ARIMA model.

## IV. CONCLUSIONS

Different from usual combined forecasting models, a new strategy for STLF of using combined models is presented in this paper. As many sequence has periodic in real life, so the SARIMA model which can dig out the periodicity contained in the data is used to predict and model the time series. Considering that the neural network has a good effect for fitting nonlinear function, so this paper uses neural network model to predict the subsequent residual sequence. At last, by using this combination method to the electricity load demand forecasting of South Australia, it shows that: this combination method has a good effect in improving the prediction precision, because it is relative to the error in 15.97% which predicted by a single SARIMA model, a hybrid model based on SARIMA and neural network reduces the load predict error to 5.12%.Simulation results demonstrate that the new strategy for STLF is effective in getting satisfying improvement of forecasting accuracy.

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