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A neural network based several-hour-ahead electric load forecasting using similar days approach

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Abstract

This paper presents a practical method for short-term load forecast problem using artificial neural network (ANN) combined similar days approach. Neural networks applied in traditional prediction methods all use similar days data to learn the trend of similarity. However, learning all similar days data is a complex task, and does not suit the training of neural network. A Euclidean norm with weighted factors is used to evaluate the similarity between the forecast day and searched previous days. According to similar days approach, load curve is forecasted by using information of the days that are similar to weather condition of the forecast day. An accuracy of the proposed method is enhanced by the addition of temperature as a major climate factor, and special attention was paid to model accurately in different seasons, i.e. Summer, Winter, Spring, and Autumn. The one-to-six hour-ahead forecast errors (MAPE) range from 0.98 to 2.43%. Maximum and minimum percentage errors, and MAPE values obtained from the load forecasting results confirm that ANN-based proposed method provides reliable forecasts for several-hour-ahead load forecasting.

Keywords: Neural network; Seasonal effect on electric load; Several-hour-ahead load forecasting; Similar days

1. Introduction

Short-term load forecast is aimed at predicting system load over a short time interval in a wide range of time leads from minutes to several days and plays an important role in the operation of power systems where basic operating functions such as energy transactions, unit commitment, security analysis, economic dispatch, fuel scheduling and unit maintenance have all benefited. The forecasting of hourly integrated load carried out for 1 day to 1 week ahead is usually referred to as short-term load forecasting [1–6]. Several approaches for the load forecast modeling have been reported in the last decades including linear regression, exponential smoothing, stochastic process, state space methods, and expert systems [7,16]. 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 [3]. Furthermore, it is difficult to model the relationships between the loads and the variables that influence the loads, such as weather or seasonal variations, holiday activities, etc. as short-term load forecasting is mainly affected by weather parameters. These are the major factors that make the modeling process complicated. Another difficulty lies in estimating and adjusting the model parameters, which are estimated from historical data that may be outmoded or may not reveal short-term load pattern changes [19,20].

Over the last decade, a great deal of attention has been devoted to the use of artificial neural networks (ANNs) to model load [2,3,5–7,12,13,17,18,21–26]. The main reason of ANN becoming so popular lies in its ability to learn complex and non-linear relationships that are difficult to model with conventional techniques. The forecast error is greatly influenced by load fluctuation and rapid change in temperature. Recently, several methods based on similarity have been reported for the purpose of load forecasting [21,22]. According to which, load curve is forecasted by using information of the days being similar to weather condition of the forecast day. These methods have an advantage of dealing not only with the non-linear part of load, but also with the weekend and special

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days. In general, the load based on several selected similar days is averaged to improve the accuracy of load forecasting [24].

This paper presents an implementation of ANN-based several-hour-ahead (one-to-six-hour-ahead) load curve forecasting using similar days approach considering the temperature as the major climate factor. The output obtained from neural network is the corrected forecasted load of similar days data. A Euclidean norm with weighted factors is used to evaluate the similarity between the forecast day and searched previous days. Special attention was paid to model accurately in different seasons of the year, i.e. Summer, Winter, Spring, and Autumn.

This paper contributes to a practical method for short-term load forecasting, especially as it shows the effect of seasonal variation on load curve forecasting. The paper is organized as follows. Section 2 gives the overview of the proposed method where we discuss selection of similar days corresponding to forecast day based on Euclidean norm. Section 3 discusses proposed neural network structure followed by load forecasting simulation results in Section 4. Conclusions are drawn in Section 5. In this paper, our analysis is based on actual load data of Okinawa Electric Power Company, Japan.

2. Selection of similar days

In this paper, we select similar days corresponding to forecast day based on Euclidean norm in which weighted factors are used to evaluate the similarity between the forecast day and searched previous days. It is useful to utilize the evaluation determined by the Euclidean norm, which makes us understand the similarity by using an expression based on the concept of norm. Decrease in Euclidean results in better evaluation of similar days. In general, the following equation is used as Euclidean norm with weighted factors:

$$D = \sqrt{\hat{w}_1(\Delta L_t)^2 + \hat{w}_2(\Delta L_s)^2 + \hat{w}_3(\Delta T_t)^2} \quad (1)$$

$$\Delta L_t = L_t - L_t^{\mathrm{p}} \quad (2)$$

$$\Delta L_{\mathrm{s}} = L_{\mathrm{s}} - L_{\mathrm{s}}^{\mathrm{p}} \quad (3)$$

$$L_{\mathrm{s}} = L_t - L_{t-1} \quad (4)$$

where L_t is the hourly load on forecast day, L_t^{p} is the hourly load on historical days, ΔL_t is the load deviation between load on forecast day and load on historical days, L_{s} is the slope between L_t and L_{t-1}, $L_{\mathrm{s}}^{\mathrm{p}}$ is the slope of historical days, ΔL_{s} is the deviation of slope between load on forecast day and load on historical days, ΔT_t is the deviation of temperature (hourly temperature) between forecast day and historical days, $\hat{w}_i$ ($i=$ 1–3) is the weighted factor, which is determined by using least square method based on the regression model that is constructed using historical temperature and load data [24,25]. Therefore, a selection of similar days that considers a trend of load and temperature is performed. The above equations give hourly calculation of Euclidean norm.

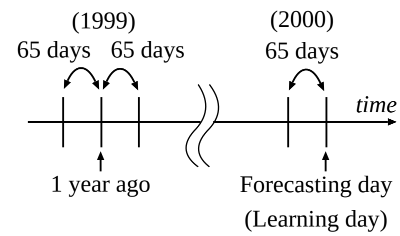

Fig. 1. Limits on the selection of similar days.

As an index for selecting the similar days, Euclidean norm with weighted factors is used in this paper. The weighted factor $\hat{w}$ is required to consider the difference of an element's unit, because the relationship between similarity and each utilized element varies with an element's unit. In the conventional papers, the maximum and minimum temperatures of the forecast day are used as variables of Euclidean norm with weighted factors. However, since maximum and minimum temperatures are forecasted temperatures, in case of rapid change in temperature on the forecast day, load changes greatly, which would cause large errors in forecasting. Therefore, we substitute load for the maximum and minimum temperatures as variable. Consequently, it is possible to select the similar load days unrelated to temperature changes by using the proposed method.

Similar days are based on the same season. The limits on the selection of similar days corresponding to forecast day are shown in Fig. 1. The past 65 days from the day before a forecast day, and past 65 days before and after the forecast day in the previous year are considered for the selection of similar days. If the forecast day is changed, similar days are selected in the same manner. It is enough to cover the limits in Fig. 1 for selecting the similar days as the load shows similarities on the same season of each year.

2.1. Procedure for selecting similar days

Step 1 Select similar days using Eq. (1).
Step 2 Load data of similar days at time $t+1$ are selected in Step 1 and assumed to be forecasted load $\bar{L}_{t+1}$ at time $t+1$.

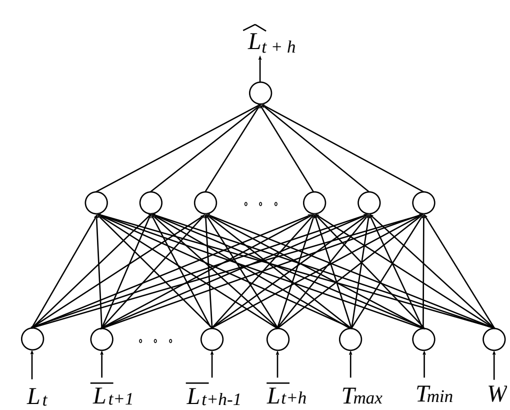

Fig. 2. Proposed neural network structure.

Table 1
Cases considered

Seasons	Selected month	Major cases
Spring	March	One-to-six-hour-ahead
Summer	July	One-to-six-hour-ahead
Autumn	October	One-to-six-hour-ahead
Winter	January	One-to-six-hour-ahead

Step 3 The value of the forecasted load that are obtained in Step 2 are assumed as actual load. Then, similar days at $t+2$ are selected by using Eq. (1) and Step 2 is repeated.

Step 4 Similarly, the forecasted load is obtained at time $t+h-1$. Then, it is assumed to be actual load and selected similar days at time $t+h$.

3. Proposed neural network architecture

The quality of the load prediction can greatly influence the quality of developed plans. Load forecasting normally uses historical load behavior to form a prediction. Historical data show a short-term correlation between the total power demand and climatic informations such as temperature, cloudiness, and wind, and sociological factors such as the day of week. The relationships between the load and these factors are difficult to determine. Because ANNs can encode complex, non-linear relations, researchers have used them to capture the relationships between the load and selected factors. Neural network employed in traditional prediction methods use all similar days data to learn the trend of similarity. However, learning all similar days data is a complex task. In this paper, to reduce the neural network structure and learning time, we propose a neural network for several-hour-ahead load forecasting as shown in Fig. 2. The network model is composed of one input layer, one hidden layer, and one output layer. Each layer has a feedforward connection. Inputs to the neural network are load, time, temperature, and weekday.

In the proposed load prediction method, we forecast the load ($\hat{L}_{t+h}$) by using neural network (Fig. 2) to modify the load curve obtained by averaging three similar load days corresponding to forecast day. The input variables of the proposed neural network structure are: mean similar days data $\bar{L}$, which is an average of three past similar days load; actual load L_t; W is a day of the week (weekday: 4, Monday: 3, Saturday: 2, Sunday: 1); and temperature ($T_{\max}$ and $T_{\min}$). In Fig. 2, h represents hour ahead (for $h=1$–6). Neural network uses the deviation of load and temperature as learning data.

Table 2
Learning parameters of neural network

Learning rate	0.6
Inertia coefficient	0.1
Learning times	1000

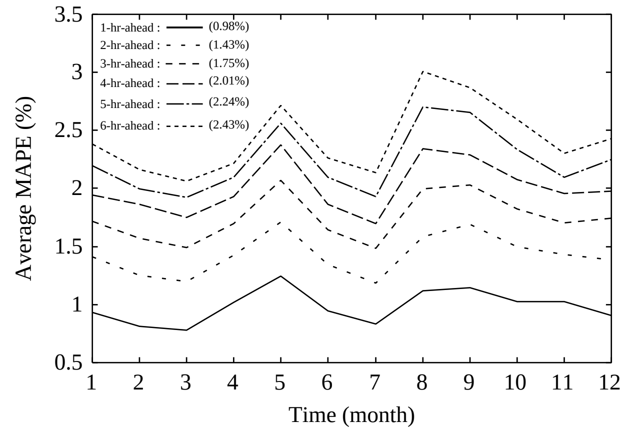

Fig. 3. Mean absolute percentage error corresponding to month.

The following energy function is used as a termination criteria during the learning procedure

$$E=\frac{1}{2}\sum(\Delta C-\Delta C^{*})^{2} \tag{5}$$

where ΔC and ΔC^* are network output and desired output, respectively.

The proposed artificial neural network (ANN) has an advantage of dealing not only with non-linear part of the load, but also with weekend and special days. In general, the load based on several selected similar days is averaged to improve the accuracy of load forecasting. Since the ANN yields correction, which is a simple data, it is not necessary for the ANN to learn all similar days data. Therefore, the ANN can forecast loads by a simple learning process. The correction from ANN is referred to as the modification of the load curves obtained by averaging similar load data corresponding to forecast day.

For learning the neural network, we adopt a well-known back propagation algorithm. The neural network model is trained by using the data of past 45 days from the day before a forecast day, and past 45 days before and after the forecast day in the previous year. The training of neural network continues unless and until the error becomes constant. After the error becomes constant, the learning procedure terminates. If the forecast time is changed, neural network is retrained to obtain the relationships between load and temperature around the forecast day.

Table 3
MAPE in different seasons

Cases	MAPE (%)			
	Summer (July 1–7)	Winter (January 1–7)	Autumn (October 1–7)	Spring (March 1–7)
One-hour-ahead	0.80	1.15	1.03	0.72
Two-hour-ahead	1.15	1.78	1.48	1.06
Three-hour-ahead	1.43	2.16	1.79	1.35
Four-hour-ahead	1.57	2.50	2.00	1.65
Five-hour-ahead	1.87	2.92	2.24	1.82
Six-hour-ahead	2.09	3.15	2.35	2.10

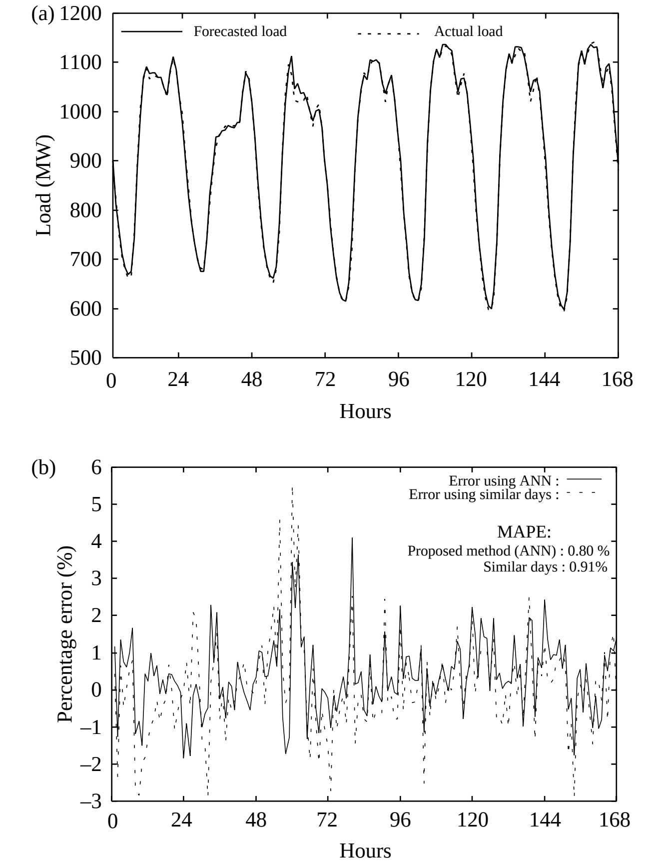

Fig. 4. One-hour-ahead forecasting results (July 1, Saturday–July 7, Friday, 2000).

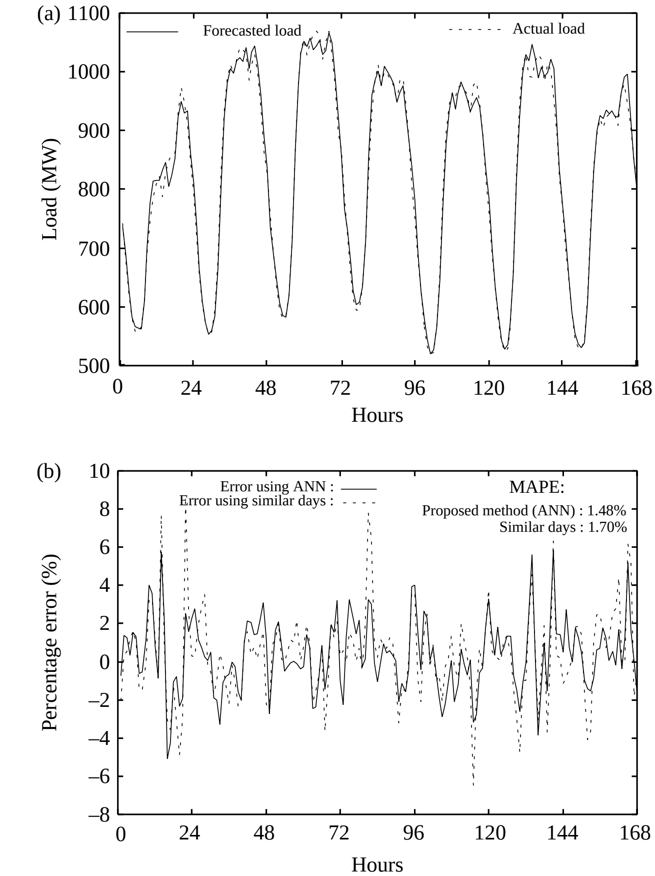

Fig. 5. Two-hour-ahead forecasting results (October 1, Sunday–October 7, Saturday, 2000).

4. Simulation results and discussion

The performance of the developed method for short-term load forecasting has been tested using the actual hourly load and temperature data (for the year 1999–2000) of Okinawa Electric Power Company, Japan. Neural network is implemented in built in-house C-programming software that was used for the numerical simulations. Load forecasting is done for the year 2000. To verify the predictive ability of the proposed method, we performed simulations for six cases (one-to-six-hour-ahead).

For the above-mentioned cases, a whole year is separated into four different seasons as Summer, Winter, Spring, and Autumn, which is presented in Table 1. March, July, October, and January are the selected months for Spring, Summer, Autumn, and Winter seasons, respectively. One-to-six-hour-ahead load forecasting is carried out for the selected month of a season considering the forecasting term as 168 h (weekly forecast). A single neural network, as shown in Fig. 2, has been used for forecasting the load in different seasons.

Since ANN is trained by using the data of past 45 days from the day before a forecast day, and past 45 days before and after the forecast day in the previous year, therefore, it is possible to obtain enough learning data. Learning parameters of the ANN are shown in Table 2, which are determined by trial and error. For BP learning of the neural network, BP learning within the specific range consists of a BP learning sets. The proposed neural network is trained by repeating BP learning set for 1000 times.

4.1. Forecasting results

The load forecast by the neural forecaster was compared to the actual load data and the error is calculated. The principal statistics used to evaluate the performance of the proposed model, mean absolute percentage error (MAPE), is defined as

$$\text{MAPE}\ (\%) = \frac{1}{N}\sum_{i=1}^{N}\frac{|L_\text{A}^i - L_\text{F}^i|}{L_\text{A}^i}\times 100 \tag{6}$$

where L_A is the actual load, L_F is the forecasted load, N is the number of hours, i is the hour index.

With the proposed technique, MAPE corresponding to months for all the cases in the year 2000 is illustrated in Fig. 3. As can be seen in Fig. 3, average MAPE results for one-to-six-hour-ahead show an increasing trend with the increase in hour-ahead forecasting.

MAPE values for one-to-six-hour-ahead forecasting in different seasons are presented in Table 3. As can be seen from Table 3, one-to-six-hour-ahead forecast error gradually

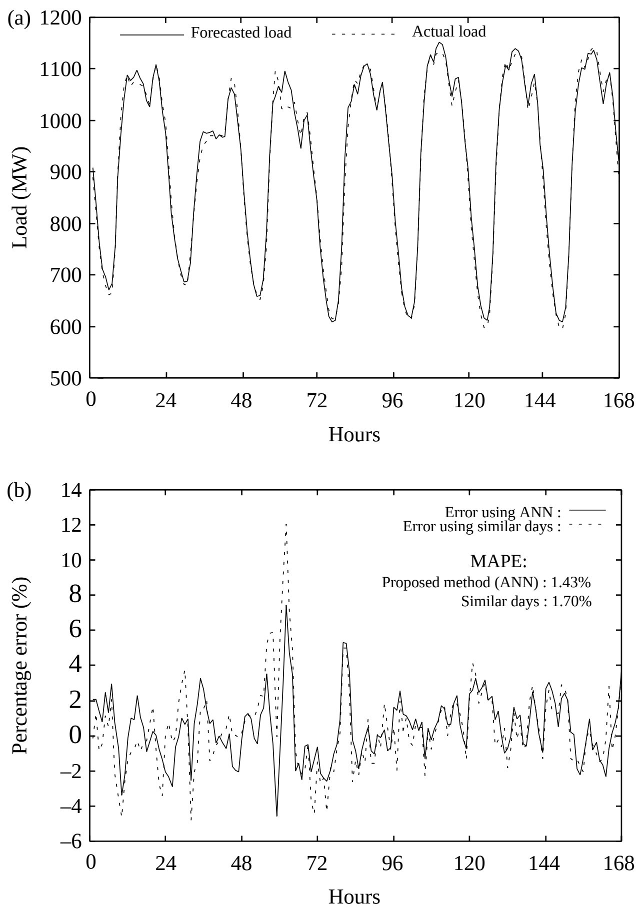

Fig. 6. Three-hour-ahead forecasting results (July 1, Saturday–July 7, Friday, 2000).

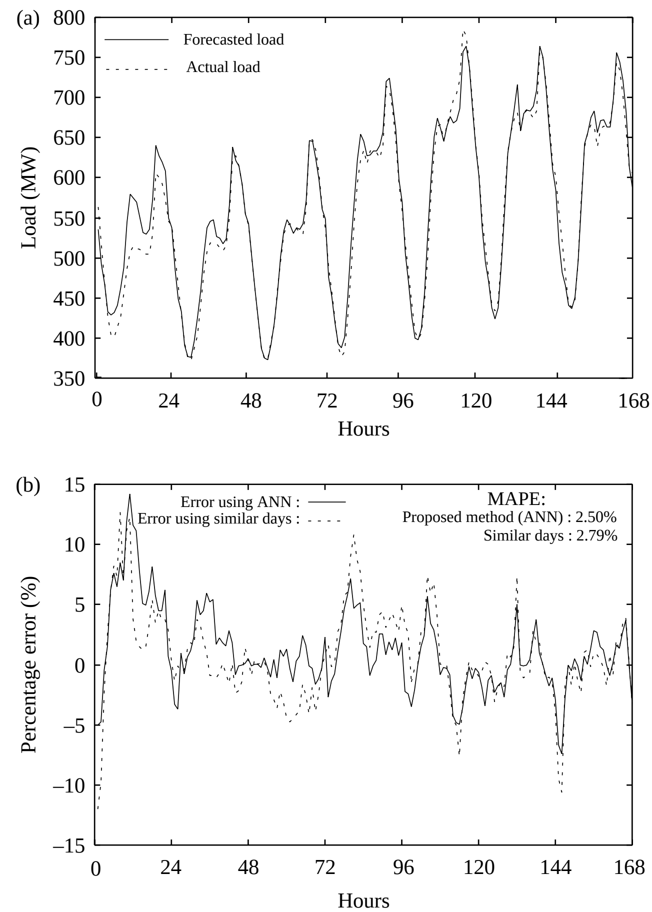

Fig. 7. Four-hour-ahead forecasting results (January 1, Saturday–January 7, Friday, 2000).

deteriorates because the error of a succeeding hour contains the error of the previous hour. It can also be observed in Table 3 that the MAPE value for Winter season is higher (3.15%) than other seasons.

The major forecasting results of the selected month of each season are shown in Figs. 4–9. Fig. 4 shows one-hour-ahead load forecasting results in summer season for the period July 1, Saturday–July 7, Friday, 2000. As can be seen from Fig. 4, the forecasted load curve almost coincides with the actual load curve, which indicates that the prediction ability of the proposed method is accurate. In the month of July, the temperature reaches maximum with high amount of humidity (in this study, the effect of humidity on electricity load has not been considered) causing increase in power demand, which is illustrated in Fig. 10, where we can observe that the power demand has suddenly risen up to around 1200 MW during July. However, forecasting errors for July are fairly small, which can be attributed to stable weather and consumption patterns. Consequently, with the proposed technique, MAPE value is obtained as 0.80%, whereas using similar days approach, it is 0.91%.

Fig. 5 shows two-hour-ahead load forecasting results in Autumn season for the period October 1, Sunday–October 7, Saturday, 2000. As can be seen in Fig. 5, the forecasted and actual load curves are closer to each other. We can also observe that power demand during the weekend is lower than that of weekdays. Power demand in Autumn season has reached up to less than 1100 MW, a bit lower than that of July. Consequently, with the proposed method using ANN, the result gives an absolute percentage error of 1.48%, whereas using similar days approach, it is 1.70%.

Fig. 6 shows the forecasting results of three-hour-ahead load forecasting for the period July 1, Saturday–July 7, Friday, 2000. If we compare Fig. 6 results with that of Fig. 4 as both are the results of same season and same month, it can be observed that percentage error in Fig. 6(b) is higher than that of Fig. 4(b). Accordingly, MAPE for three-hour-ahead is obtained as 1.43%, which is higher than that obtained for one-hour-ahead (0.80%). Note that MAPE result here shows an increasing trend with the increase in hour-ahead forecasting. This is because of the presence of previous hour error in the error of a succeeding hour.

Figs. 7 and 8 show four-hour-ahead and five-hour-ahead load forecasting results in Winter and Spring seasons for the period January 1, Saturday–January 7, Friday, 2000 and March 1, Wednesday–March 7, Tuesday, 2000, respectively. From these figures, we can observe accuracy in the forecasted load

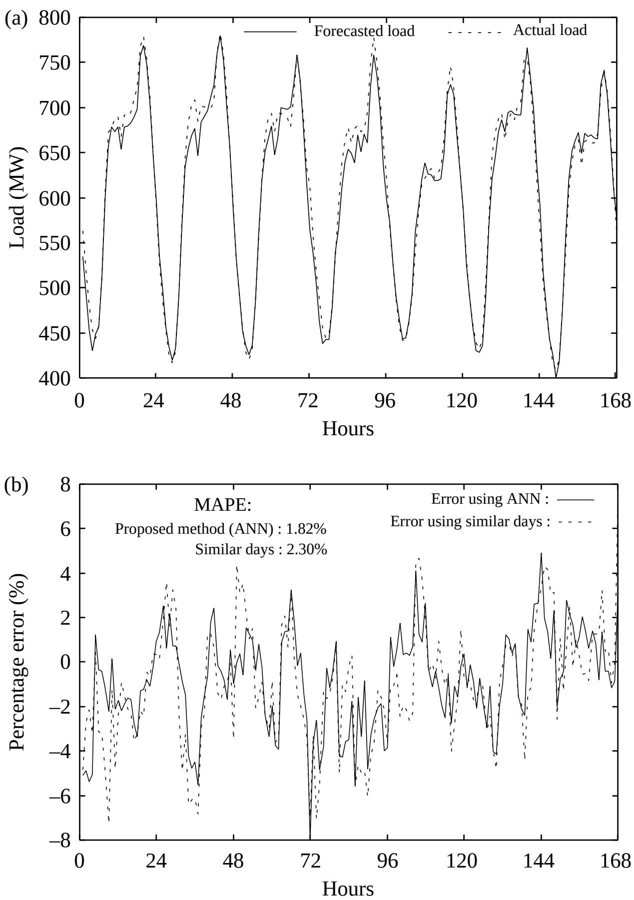

Fig. 8. Five-hour-ahead forecasting results (March 1, Wednesday–March 7, Tuesday, 2000).

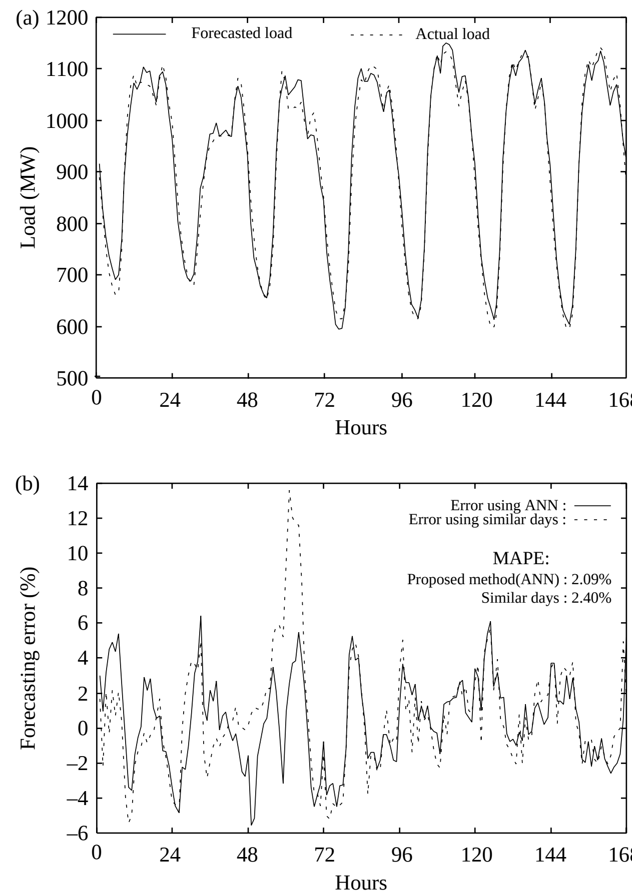

Fig. 9. Six-hour-ahead forecasting results (July 1, Saturday–July 7, Friday, 2000).

curves. Power demand is found to be reduced during Winter season when compared with other seasons. Consequently, the result gives an absolute percentage error of 2.50% for four-hour-ahead load forecasting in Winter season, whereas it is 1.82% for five-hour-ahead load forecasting in Spring season. Similarly, Fig. 9 shows six-hour-ahead load forecasting results for the period July 1, Saturday–July 7, Friday, 2000 where MAPE value is obtained as 2.09%.

Percentage errors obtained in each case by using the proposed ANN method is compared with that of similar days approach. It can be observed from Figs. 4(b), 5(b), 6(b), 7(b), 8(b), and 9(b) that by the application of proposed ANN method, a reduction in error can be achieved in an efficient way to obtain the accurate forecasted load.

Table 4 presents maximum (max.) and minimum (min.) percentage errors in each selected season. Maximum percentage error in Winter season is found to be comparatively higher than other seasons. MAPEs, maximum and minimum percentage errors indicate that the proposed prediction method is accurate in forecasting hourly loads. Results obtained in Tables 3 and 4 are based on true temperature information because all data are historical.

The proposed approach has a significant benefit. The algorithm is simple. The key equation in this algorithm is the Euclidean norm equation (1). All of these are easily programmed in a computer. Also, the algorithm is highly efficient from a computational point of view. From the above results, we can say that large forecasting errors are improved by the proposed method. The experience acquired from the development of ANN-based proposed method provides more reliable forecasts for several-hour-ahead load forecasting.

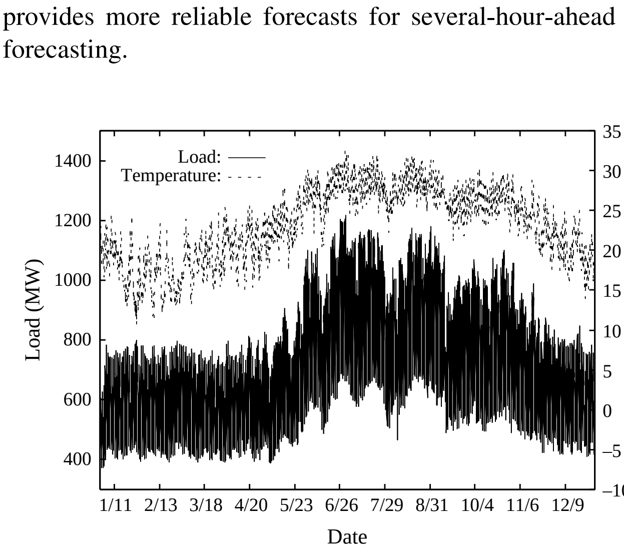

Fig. 10. Actual load and temperature variations in Okinawa during 2000.

Table 4
Maximum and minimum percentage errors in each season

Cases	Max. and min. percentage errors (%)							
	Summer (July)		Winter (January)		Autumn (October)		Spring (March)	
	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.
Case1	4.77	−3.95	5.42	−4.55	6.16	−4.91	4.79	−3.94
Case2	6.02	−5.16	7.96	−7.06	5.79	−6.06	8.36	−4.98
Case3	8.23	−9.59	11.84	−8.19	7.25	−7.34	10.53	−5.75
Case4	8.64	−9.88	14.21	−9.10	8.97	−7.49	9.76	−5.71
Case5	8.79	−10.62	14.36	−8.43	9.13	−8.03	9.28	−7.96
Case6	8.72	−13.19	17.19	−8.87	12.08	−7.12	8.05	−8.08

5. Conclusions

In addition to the traditional forecasts of hourly integrated loads for the next several days, the instantaneous load predictions for the next several hours are also required to operate the power system reliably and economically. This paper presented a practical method for short-term load forecasting. The method is based on artificial neural network (ANN) combined similar days approach, which achieved a good performance in the very special region. The Euclidean norm with weighted factors is used to evaluate the similarity between the forecast day and searched previous days. To verify the predictive ability of the proposed method, we performed simulations for six cases, i.e. one-to-six-hour ahead load forecasting. Special attention was paid to model accurately in different seasons of the year, i.e. Summer, Winter, Spring, and Autumn. MAPEs results showed the clear increasing trend with the increase in hour ahead. The sample average of MAPEs for one-hour-ahead forecasts is 0.98%. This figure increases to only 2.43% for six-hour-ahead predictions. The forecaster performs well in the case of sudden weather changes.

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