One-Hour-Ahead Load Forecasting Using Neural Network

Tomonobu Senjyu, *Member, IEEE*, Hitoshi Takara, Katsumi Uezato, and Toshihisa Funabashi, *Senior Member, IEEE*

***Abstract*—Load forecasting has always been the essential part of an efficient power system planning and operation. Several electric power companies are now forecasting load power based on conventional methods. However, since the relationship between load power and factors influencing load power is nonlinear, it is difficult to identify its nonlinearity by using conventional methods. Most of papers deal with 24-hour-ahead load forecasting or next day peak load forecasting. These methods forecast the demand power by using forecasted temperature as forecast information. But, when the temperature curves changes rapidly on the forecast day, load power changes greatly and forecast error would going to increase. In conventional methods neural networks uses all similar day's data to learn the trend of similarity. However, learning of all similar day's data is very complex, and it does not suit learning of neural network. Therefore, it is necessary to reduce the neural network structure and learning time. To overcome these problems, we propose a one-hour-ahead load forecasting method using the correction of similar day data. In the proposed prediction method, the forecasted load power is obtained by adding a correction to the selected similar day data.**

***Index Terms*—Load forecasting, recurrent neural network, on-line learning.**

I. Introduction

LOAD forecasting has always been the essential part of an efficient power system planning and operation. Several electric power companies have adopted the conventional methods for forecasting the future load [1]. In conventional methods, the models are designed based on the relationship between load power and factors influencing load power. The conventional method has the advantage that we can forecast load power with a simple prediction model. However, since the relationship between load power and factors influencing load power is nonlinear, it is difficult to identify its nonlinearity by using conventional methods.

Recently, several methods based on similarity have been reported for load forecasting [2]–[5]. These methods are based on similarity forecast future power load curve by using information of the day being similar to weather condition of forecast day. These methods have the advantage of dealing with not only the nonlinear part of load power, but also with weekend and special days, etc. In prediction methods based on similarity, the load power on several selected similar days are averaged to improve the accuracy of load forecasting. However, if there is a considerable error between the load power on a forecast day and that on similar days, we are not able to expect the good prediction accuracy for averaging the load power on similar days.

Several approaches have been studied using neural networks for load forecasting [6]–[8]. Neural network are suitable for load forecasting because of their approximation ability for nonlinear mapping and generalization. Most of these neural network based methods, reported so far uses weather information, load power of the day before forecast day and day type for input variables. Therefore, it is difficult to forecast future load in weekend and special day, since neural network reported so far must deal with a lot of information.

Most of the papers deal with 24-hour-ahead load forecasting or next day peak load forecasting. These methods forecast the demand power by using a forecasted temperature as forecast information. But in case of rapid changes in temperature on the forecast day, load power changes greatly and forecast error would going to increase. Therefore, in this case, one-hour-ahead load forecasting which uses the temperature of a forecast day as forecast information is effective.

Neural networks which are used in conventional methods uses all similar day's data to learn the trend of similarity. However, learning of all similar day's data is a complex task, and it does not suit learning of neural network. Therefore, it is necessary to reduce the neural network structure and learning time.

To overcome the problems mentioned above we propose a one-hour-ahead load forecasting method using the correction of similar day data in this paper. In the proposed prediction method, the forecasted load power is obtained by adding a correction to the selected similar day data. The correction is yielded from the neural network. Since the neural network yields the correction which is a simple data, it is not necessary for the neural network to learn all similar day's data. Therefore, the neural network can forecast load power by simple learning. If the forecast day is changed, the neural network is retrained and it can obtain the relationship between load and temperature around the forecast day. Therefore, it is possible to deal with seasonal change by using the proposed neural network. The suitability of the proposed approach is illustrated through an application to the actual load data of Okinawa Electric Power Company in Japan.

II. Selection of Similar Days

In this paper, Euclidean norm with weighted factors is used to evaluate the similarity between a forecast day and a searched previous day. It is useful to utilize evaluation, determined by the Euclidean norm which makes us understand the similarity

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T. Senjyu, H. Takara, and K. Uezato are with the Department of Electrical and Electronics Engineering, Faculty of Engineering, University of the Ryukyus, Okinawa, Japan (e-mail: b985542@tec.u-ryukyu.ac.jp.)

T. Funabashi is with Meidensha Corporation, Tokyo, Japan (e-mail: funabashi-t@honsha.meidensha.co.jp.)

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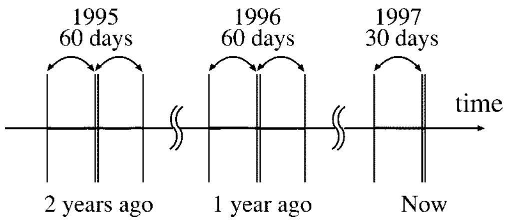

Fig. 1. Input used to produce this paper.

by using an expression based on the concept of norm. We select similar days corresponding to a forecast day based on Euclidean norm. Therefore, the more Euclidean norm decreases, the better evaluation of similar day becomes. We have studied the correlation coefficient between weather data and load power before the application of Euclidean norm. In general, the following equation is utilized as Euclidean norm with weighted factors:

$$D = \sqrt{\hat{w}_1(\Delta L^t)^2 + \hat{w}_2(\Delta L^{t-1})^2 + \hat{w}_3(\Delta L^{t-2})^2} \quad (1)$$

$$\Delta L^{t-k} = L_{t-k} - \tilde{L}^p_{t-k} \quad (2)$$

where L_{t-k} is the load curve on a forecast day, $\tilde{L}^p_{t-k}$ is the load curve on a similar day, ΔL^{t-k} is the deviation of load between load power on the forecast day and load power on a similar day. $\hat{w}_i$ $(i = 1–3)$ is the weighted factor. The weighted factor $\hat{w}_i$ is determined by the least square method based on regression model, that is constructed using the past temperature and load data. Therefore, a selection of similar days that consider a trend of load and temperature is performed.

As an index for selecting of similar days, Euclidean norm with weighted factors is used in this paper. In conventional papers, as variables of Euclidean norm with weighted factors, the maximum and minimum temperature of forecast day is used. However, since maximum and minimum temperature are forecasted temperatures, in case of rapid changes in temperature on the forecast day, load power changes greatly and forecast error would going to increase. Therefore, in this paper, we substitute load power for the maximum and minimum temperature as variables. Consequently, it is possible for the proposed prediction method to select similar days unrelated to temperature changes.

The limits of selection of the similar days corresponding to a forecast day are shown in Fig. 1. It is enough to cover the limits in Fig. 1 for selecting the similar days. Since the variety of load power shows similarity on same season of each year.

III. Neural Network

A. Structure of Neural Network

The neural network employed in conventional methods uses all similar day's data to learn the trend of similarity. However, learning all similar day's data is a complex task. To reduce the neural network structure and learning time, we propose a neural network model which is shown in Fig. 2.

Generally, neural networks with three layers have approximation ability for a nonlinear function because of increasing the number of the hidden units. Therefore, the model shown in Fig. 2 is composed of three layers, and each layer has a feedforward connection. In this model, the number of input units is 9, hidden units of 20, and one output unit.

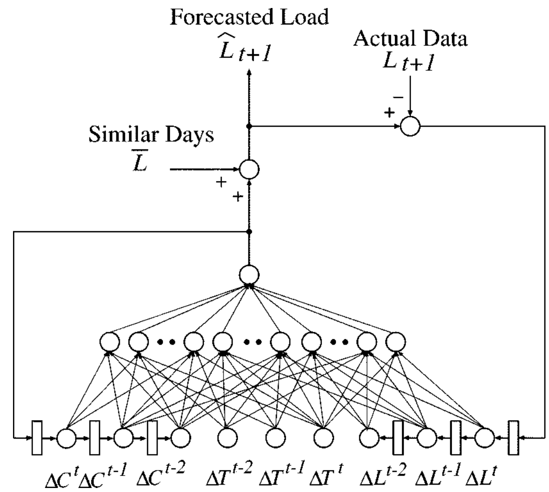

Fig. 2. Neural network model.

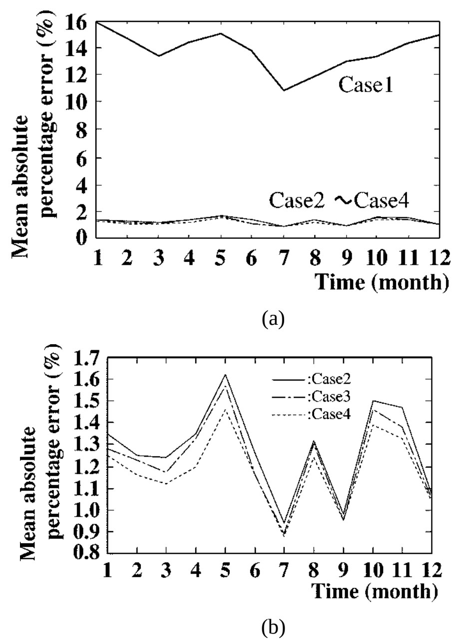

Fig. 3. Mean absolute percentage error corresponding to month.

TABLE I
Mean Absolute Percentage Error in 1997

1997	MAPE (%)
Case 1	13.08
Case 2	1.28
Case 3	1.23
Case 4	1.18

In the proposed prediction method, the forecasted load power is obtained by adding a correction to the selected similar day data. Where, the correction is obtained from the neural network. The neural network uses the deviation data of load power and the deviation data of temperature as learning data. Therefore, it is possible to reduce the neural network structure and learning time. Also, this method forecast load curve using the neural network, which adopt on-line learning. Then, feedback data and forecast error are used as learning data for the on-line learning.

The variables of the proposed neural network are the forecasted load $\hat{L}_{t+1}$, similar day's data that are averaged with using selected five similar days $\bar{L}$, actual load L_{t+1}, deviation in temperature between the forecast day and on a similar day ΔT^{t-k}, correction for forecasting load ΔC^{t-k}, deviation of power between the forecast day and on a similar day ΔL^{t-k} $(k = 0\text{–}2)$

$$\Delta L^{t-k} = \hat{L}_{t+1} - L_{t+1} \tag{3}$$
$$\Delta T^{t-k} = T_{t-k} - T^{p}_{t-k} \tag{4}$$

where, T_{t-k} is the temperature on a forecast day and T^{p}_{t-k} is the temperature on similar days.

B. Learning and Forecasting Procedures

For learning the neural network, we adopt the back propagation algorithm. The neural network is trained by using the data of past 30 days from the day before a forecast day, and past 60 days before and after the forecast day in the previous year. If the forecast day is changed, the neural network is retrained and it can obtain the relationship between load and temperature around forecast day. Therefore, it is possible to deal with seasonal change by using the proposed neural network. Learning and forecasting procedures for the proposed neural network are as follows.

- Step 1) *Determine the learning range of the neural network:* The neural network is trained by using the data of past 30 days from the day before forecast day and past 60 days before and after forecast day in previous year.
- Step 2) *Determine the limits of selection of similar days for one learning day:* The limits of selection of similar days for one learning day is the past 30 days from the day before a learning day and past 30 days before and after a learning day in previous year.
- Step 3) *Select similar days for the first learning day:* For the first learning day, N similar days are selected from the limits of selection of similar days. (We select 10 similar days in this paper.)
- Step 4) *Back propagation learning for N similar days:* Neural network is trained by using N similar days for the one learning day.
- Step 5) *Back propagation learning for all the days of learning range:* Neural network is trained for all the days of learning range in the same method as in *Step 3* and *4*.
- Step 6) *200 iteration of BP learning within the specific range:* BP learning within the specific range consists of a BP learning set. Neural network is trained by repeating the BP learning set 200 times.
- Step 7) *Select similar days for forecast day:* Before forecasting load curve, we select M similar days corresponding to the forecast day (we select five similar days in this paper).
- Step 8) *Input variables of neural network:* Input variables of the neural network are as follows. ΔT^{t-k} is the deviation temperature between on the forecast day and on a similar day, ΔL^{t-k} is the deviation load power between on the forecast day and on a similar day, ΔC^{t-k} is the correction for forecasting load.
- Step 9) *Forecasting correction:* Input variables which are described in *Step 8* are used in the trained neural network. Also, we can obtain a correction.
- Step 10) *Forecasting load curve:* We can obtain the forecasted load curve by adding a correction to the selected similar day data.

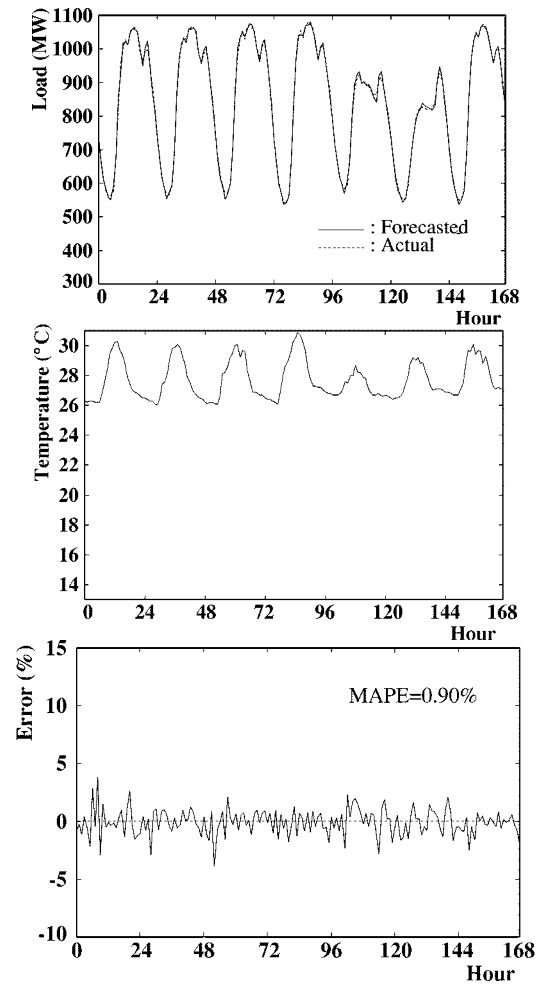

Fig. 4. Forecasting result (7/1–7/7 1997).

IV. SIMULATION RESULTS

To verify the predictive ability of the proposed method, we perform simulations for Case 1 to Case 4. The data used in the simulations in the actual load power data of Okinawa Electric Power Company and temperature data from 1995 to 1997. We forecast the load power in 1997. Case 1 to Case 4 are indicated as follows.

- Case 1) Forecast load curve using a simple regression model. To construct that model, past temperature and load data is used.
- Case 2) Forecast load curve using only similar day data. Then, the neural network is not used.
- Case 3) Forecast load curve using the neural network which adopts off-line learning. Then, only similar day data is used as learning data for off-line learning.

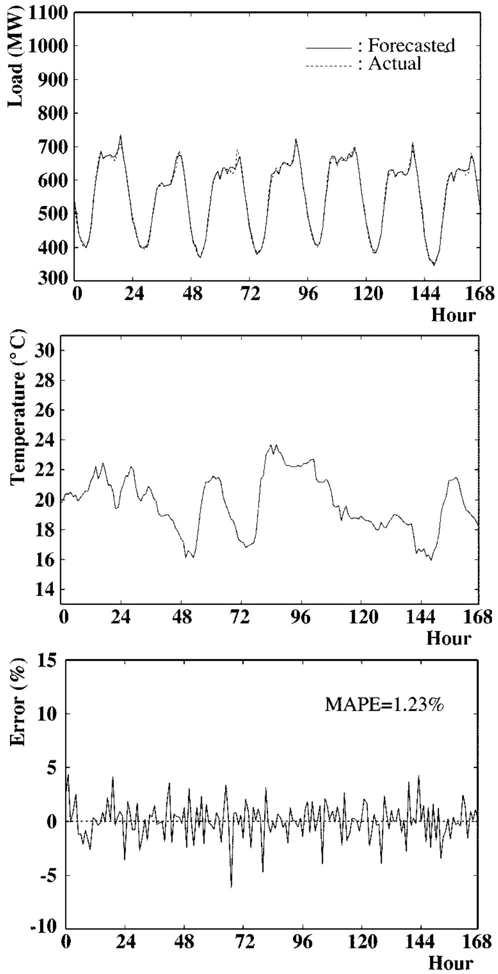

Fig. 5. Forecasting result (4/5–4/11 1997).

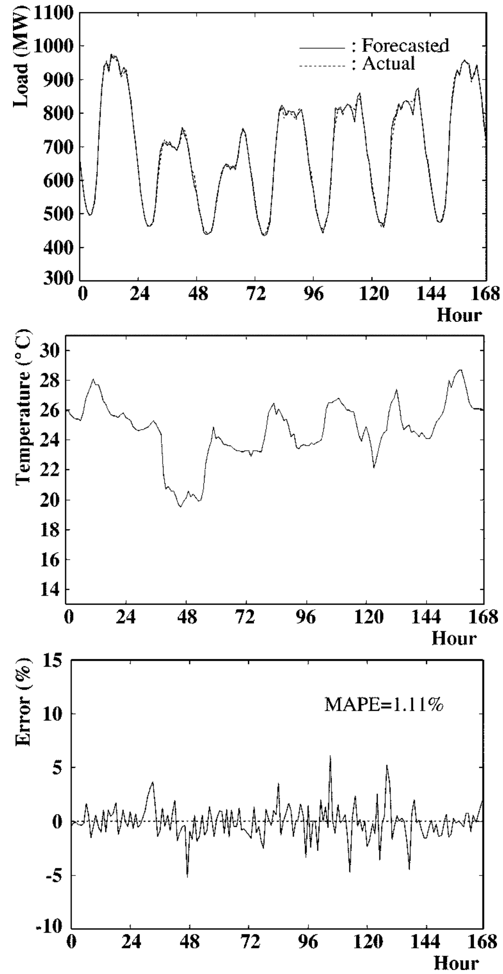

Fig. 6. Forecasting result (9/26–10/2 1997).

Case 4) Forecast load curve using the neural network which adopt on-line learning. Then, feedback data and forecast error are used as learning data for on-line learning.

The neural network is trained by using the data of past 30 days from the day before forecast day, and past 60 days before and after forecast day in previous year.

The mean absolute percentage error (MAPE) with the proposed technique is shown in Fig. 3. Fig. 3(a) shows forecasted results for Cases 1 to 4. However, so it is difficult to know the changes in Case 1, Case 2, and Case 3 from Fig. 3(a), we draw a new figure, Fig. 3(b). Fig. 3(b) shows forecasted results for Case 2 to Case 4 conditions. The MAPE is defined as follows:

$$\mathrm{MAPE}(\%) = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|P_A^i - P_F^i\right|}{P_A^i} \times 100 \tag{5}$$

where P_A is the actual load, P_F is the forecasted load, and N is the number of data.

The mean absolute percentage error for Case 1 to Case 4 in the year 1997 are shown in Table I. We can see from Fig. 3 and Table I that the prediction ability for Case 4 is better than any one (Case 1, Case 2, and Case 3). Particularly, we can notice the prediction ability Case 4, which is better than that for other cases on March, May, and October, in which weather changes are seasonal.

Generally, there are few data on actual load and temperature data in weekend and national holidays, which are used for training of the neural network. Therefore, since a neural network cannot deal with many data for weekend and national holidays forecast error would going to increase. However, in the proposed prediction method, the neural network is trained for selected 10 similar day's data for each learning day of learning range. Therefore, we can get necessary data for learning on weekend and national holidays with improved forecasting accuracy.

We can observe from Fig. 4, that a change of load and temperature is regular in this term. We can notice that, the neural network which uses load and temperature as input variables can easily be trained to the load trend and output a proper correction. We can see from Fig. 4 that the forecast error is 0.9%.

Figs. 5 and 6 show the load forecasting for are week term when the load on term that load and temperature changes are irregular. The training of neural network, which uses temperature as input variable become complex and there is a possibility that the neural network cannot output a proper correction. However, since the proposed prediction method adopt on-line learning algorithm, the neural network can learn the relationship between rapid temperature changes and forecast error. Therefore, the neural network which is used in the proposed prediction method can output a proper correction.

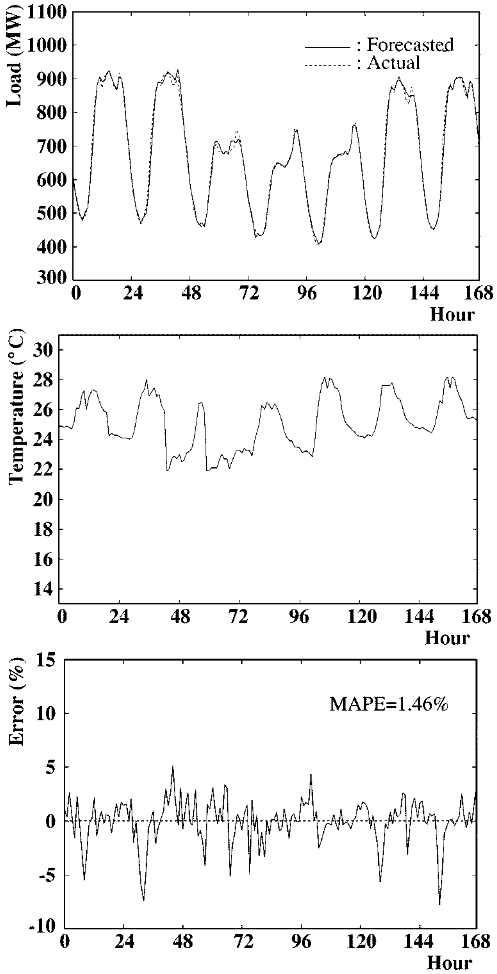

Fig. 7. Forecasting result (5/1–5/7 1997).

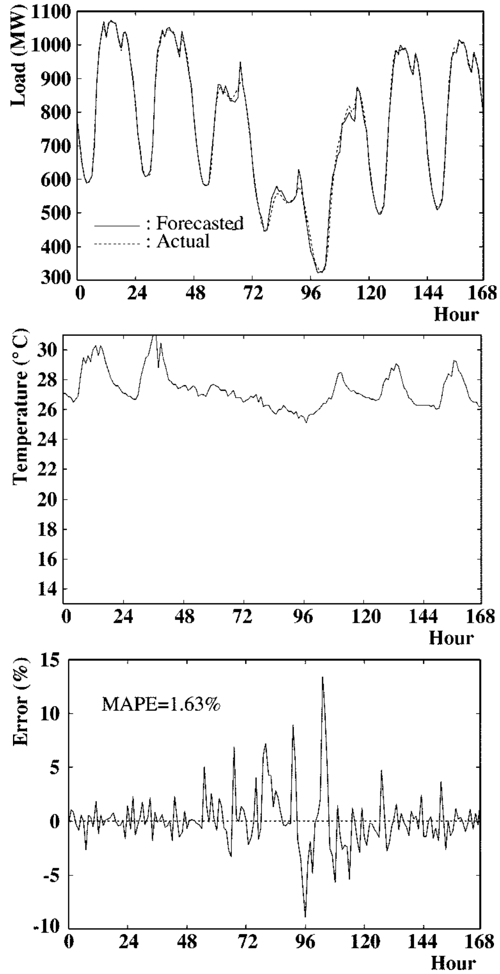

Fig. 8. Forecasting result (8/14–8/20 1997).

The results of forecasted load on consecutive holidays and special days are shown in Figs. 7 and 8. In the first week of May, seasonal change is large and weather is changeable. Also, since this term includes consecutive holidays, it is difficult to forecast load on this term. Especially, since the load reduces large in from 3 to 5 in May, there were few data corresponding to forecast day within the limit of selection of similar days. However, we can see from Fig. 7 that forecast error is small. So 3 and 4 in 1997, May is Saturday and Sunday, respectively, we can notice that the influence of consecutive holidays for forecasting accuracy is small. We can observe from Fig. 8, that the forecast error is increased, indicating the influence of typhoon. Then forecast error are around 14% in maximum and 1.63% on average. However, we can see from Fig. 8 that the proposed prediction method can forecast exactly maximum and minimum load. We can also see that since, the neural network use load power as input variables, it is possible to output a proper correction corresponding to rapid load changes. It is also possible to obtain lots of learning data in consecutive holidays and special day.

V. Conclusion

In the proposed prediction method, the forecasted load power is obtained by adding a correction to the selected similar day data. Since, the neural network output a correction which is small data, it is not necessary for the neural network to learn all the similar day's data. Therefore, it is possible to reduce the neural network structure and learning time. If the forecast day is changed, the neural network is retrained and it can obtain the relationship between load and temperature around forecast day. Therefore, it would be able to output the correction, that corresponding to the rapid temperature changes.

To verify the effectiveness of the proposed prediction method, we adopt the term in which temperature change is irregular and special days as the forecasting term. The proposed approach in this paper can be applied to each forecasting term. The suitability of the proposed approach is illustrated through an application to the actual load data of the Okinawa Electric Power Company in Japan.

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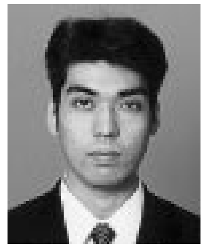
Tomonobu Senjyu (A’89) was born in Saga, Japan, in 1963. He received the B.S. and M.S. degrees in electrical engineering from the University of the Ryukyus, Okinawa, Japan, in 1986 and 1988, respectively, and the Ph.D. degree in electrical engineering from Nagoya University, Nagoya, Japan, in 1994.

Since 1988, he has been with the Department of Electrical and Electronics Engineering, Faculty of Engineering, University of the Ryukyus, where he is currently a Professor. His research interests are in the areas of stability of ac machines, advanced control of electrical machines, power electronics, and development of renewable energy.

Dr. Senjyu is a member of the Institute of Electrical Engineers of Japan.



Hitoshi Takara was born in Okinawa, Japan, in 1977. He received the B.S. degree in electrical engineering from the University of the Ryukyus, Okinawa, Japan, in 2000. Currently, he is pursuing the M.S. degree in the Department of Electrical and Electronics Engineering, University of Ryukyus.

His research interests are in the areas of load forecasting.

Katsumi Uezato was born in Okinawa, Japan, in 1940. He received the B.S. degree in electrical engineering from the University of the Ryukyus, Okinawa, Japan, the M.S. degree in electrical engineering from Kagoshima University, Kagoshima, Japan, and the Ph.D. degree in electrical engineering from Nagoya University, Nagoya, Japan, in 1963, 1972, and 1983, respectively.

Since 1972, he has been with the Department of Electrical and Electronics Engineering, Faculty of Engineering, University of the Ryukyus, where he is currently a Professor. He is engaged in research on stability and control of synchronous machines and renewable energy development.

Dr. Uezato is a member of the Institute of Electrical Engineers of Japan.

Toshihisa Funabashi (M’90–SM’96) was born in Aichi, Japan, on March 25, 1951. He received the B.S. degree in electrical engineering from Nagoya University, Aichi, Japan, in 1975. He received the Doctor degree in electrical engineering from Doshisha University, Kyoto, Japan, in 2000.

In 1975, he joined Meidensha Corporation, Tokyo, Japan, where he was engaged in research on power system analysis and is currently Senior Engineer of the Power System Engineering Division.

Dr. Funabashi is a chartered engineer in the U.K. and a member of the IEE and the IEE of Japan.