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Mid-term Load Pattern Forecasting With Recurrent Artificial Neural Network

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ABSTRACT The paper describes a mid-term daily peak load forecasting method using recurrent artificial neural network (RANN). Generally, the artificial neural network (ANN) algorithm is used to forecast short-term load pattern and many ANN structures have been developed and commercialized so far. Otherwise, learning and estimation for long-term and mid-term load forecasting are hard tasks due to lack of training data and increase of accumulated errors in long period estimation. The paper proposes a mid-term load forecasting structure in order to overcome these problems by input data replacement for special days and a recurrent-type NN application. Also, the proposed RANN gives good performances on estimating sudden and nonlinear demand increase during heat waves. The results of case studies using load data of South Korea are presented to show performances and effectiveness of the proposed RANN.

INDEX TERMS Intelligent system, mid-term load forecasting, nonlinear load response, recurrent artificial neural network.

I. INTRODUCTION

Accurate load forecasting becomes essential for an effective power system management and planning overhauls of the generators in a situation that the power consumption steeply increases and electric power reserve rate becomes insufficient. The load forecasting issues are to solve a complex nonlinear relationship related to previous load demand, social variation, and weather variation. Therefore, it still remains a challenging task to accurately forecast loads in order to supply high quality electric energy to customers in a secure and economic manner [1].

The purpose of load forecasting is generally divided into three categories: short-term, mid-term, and long-term load forecasting. Short-term load forecasting focuses on load variation from one hour to one week. Mid-term load forecasting interests in load estimation from one week to a month and long-term load forecasting can be extended to from one month to several years. The reason why the load forecasting is divided into several categories is that the estimation result from each method can be used in different operation objects. The short-term load forecasting is useful to control and schedule power generation for all generators in the system and also needed to estimate load flows and make decisions to prevent overloading on power facilities. The load forecasting for the mid-term and long-term is important to determine consequential power generation, the capacity of load consumption, and expansion of power facilities such as generators, transmission lines, and substations [2].

On the other hand, artificial neural network (ANN) has been much attracted in forecasting electric power demand. The ANN has become popular in load forecasting because it has ability to learn complex and nonlinear relationships that cannot be captured with the conventional techniques. Most papers regarding load forecasting with ANN focus on load forecasting for several hours or a few days ahead [3]–[12]. Also, some papers deal with similarity based load forecasting in order to reduce training and estimation errors [4], [13]. In effect, the daily peak load correlates intimately with loads from the last few days and the further the date is from the estimation day, the less correlation between loads becomes. Therefore, the ANN method is generally suitable for short-term load forecasting.

There have been several researches regarding application of the ANN to mid-term load forecasting [14]–[16]. However, learning and estimation for mid-term load forecasting are hard tasks due to lack of training data and increase of accumulated errors on long period estimation. This means

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that input data with strong correlation with the load on the forecasted day cannot be easily obtained because the daily peak load is closely related to loads from the last few days.

In the paper, the recurrent type ANN (RANN) is proposed to estimate mid-term load demand in order to overcome these problems with limited input data such as recorded load and temperatures. In order to get large input data and enhance convergence of the ANN algorithm, load values of special days and weeks are replaced with artificially processed normal data. The proposed algorithm recurrently uses the output data as input data and weekly pattern is also used as input data in order to prevent increase of accumulated errors on a long period estimation. In the paper, the proposed RANN has been implemented by writing code with MATLAB® software. Then, the results of case studies using load data of South Korea are presented to show performances and effectiveness of the proposed RANN in comparison with the results of commercial software (KPX short-term load forecaster, KSLF) [17]–[19]. Moreover, the proposed RANN having an ability to train nonlinear pattern gives good performances on estimating sudden demand increase during heat waves.

The paper is organized as follows: Section II presents a selection of input data in order to overcome lack of training data and a forecasting structure with the RANN. Then, simulation results of case studies with practical load are given in Section III. Finally, the conclusions are given in Section IV.

II. SELECTION OF INPUT DATA

In all kinds of load forecasting problems, selecting proper input data is very important issue. Some papers proposed a method to find similar days based on Euclidean norm and used the similar days as input data of load forecasting algorithm [4], [13]. Also, some papers suggested the use of load patterns of the nearest three days as inputs because they have large correlation with the load of the forecasting day [17]. However, as those approaches are well-suited for short-term load forecasting, they can reduce consistency of input and have difficulty with making a consistent structure for load forecasting in mid-term forecasting.

A. REPLACEMENT OFR SPECIAL DAYS AND WEEKS

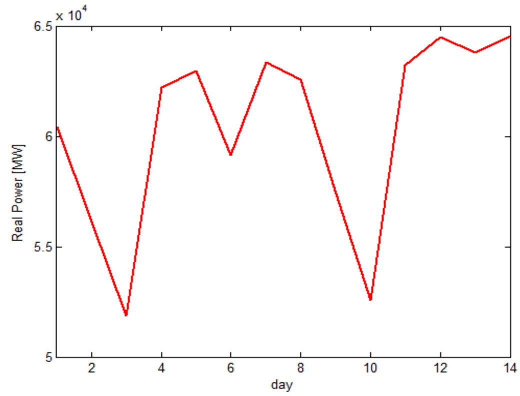
In order to get large input data and enhance convergence of the ANN algorithm, load values of special days and weeks are needed to be replaced with artificially processed normal data. This process can improve the quality of ANN algorithm training ordinary load patterns and reduces training errors of the ANN dramatically. As mentioned above, the purpose of the paper is to forecast the ordinary mid-term load demand, which is essential for effective power system management and planning overhauls of the generators. The paper does not need to deal with the load forecasting of the special days and weeks within the target range in mid-term load forecasting. Actually, they are different issues with solving load forecasting problem. In practical application, they can be accurately estimated based on the algorithms in [17]–[19], which have already been commercialized.

In the paper, the load demands of special day and week are replaced by Eqs. (1) and (2), respectively.

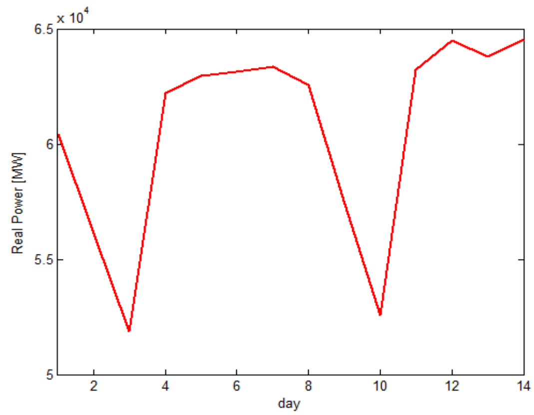
$$L'_D = \frac{L_{D-1} + L_{D+1}}{2} \tag{1}$$

$$\begin{bmatrix} L'_D \\ \vdots \\ L'_{D+6} \end{bmatrix} = \left(\begin{bmatrix} L_{D-7} \\ \vdots \\ L_{D-1} \end{bmatrix} + \begin{bmatrix} L_{D+7} \\ \vdots \\ L_{D+13} \end{bmatrix} \right) /2 \tag{2}$$

where L without a superscript, $'$, means real data and L' means replaced data. D is a base day for the replacement.



(a) Load demand of a special day



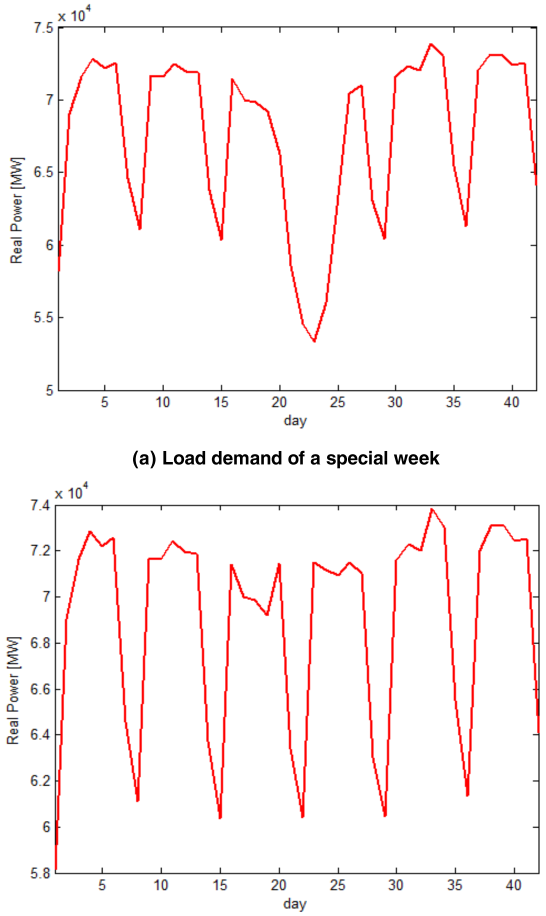
(b) Replaced load data instead of a special day

FIGURE 1. Example of load replacement of special day.

With Eqs. (1) and (2), the load demands of the special day and week become ordinary load demands. Figures 1 and 2 show examples of the load data before and after load data replacement. As shown in the figures, the inconsistent data is replaced with the consistent data. This process improves the quality of the ANN algorithm training general load pattern and extends forecasting terms further ahead.

B. INPUT DATA AND ESTIMATION PROCESS

The focus of the paper is to forecast daily peak loads for four weeks. As mentioned in introduction, loads that are highly correlated with the target day are typically within seven days. This means that we cannot obtain the high correlated data



(a) Load demand of a special week

(b) Replaced load data instead of a special week

FIGURE 2. Example of load replacement of special week.

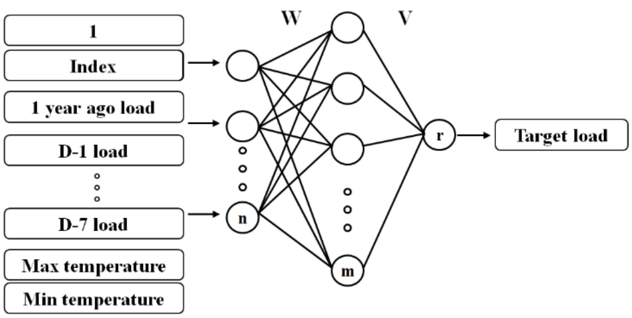


FIGURE 3. Structure for mid-term load forecasting.

from recorded data except the first week among four weeks. Therefore, it is not easy to predict load data beyond a week. Therefore, the key is that the error should not increase even if the day to be predicted is further away from the day forecast is done.

Selected input data based on various case studies is illustrated in Fig. 3. Note that the input data cannot be systematically defined in neural network application especially for load forecasting. First constant '1' is entered together. It is a kind of bias input helping set the offset for learning [20]. The effectiveness of the bias input will be explained in next section with an example. Also, week index [1, 2, …, 7] is used to learn weekly repeatability. Load data on the same day a year ago must be used for the ANN to learn yearly pattern. Load data of the last seven days with high correlation must be entered. Since minimum temperature as well as maximum temperature during a day are important factors in demand response, both should be used to improve learning accuracy. Finally, the number of inputs is twelve and the thirty hidden neurons are determined by various tests.

As shown in Fig. 3, the first layer receives the twelve inputs and distributes them to the hidden layer, which has thirty hidden neurons, via weight matrix **W**. The data reaching at the hidden layer is the input variable for the sigmoidal function in Eq. (3). Then, the outputs of each of the hidden neurons are in turn fed via weight matrix **V** to the output layer.

$$S(x) = \frac{1}{1+\exp(-x)} \tag{3}$$

where x and $s(x)$ are input and output of the hidden neuron, respectively.

As shown in Fig. 3, the proposed structure needs load data for the last seven days to estimate daily loads. Therefore, the paper proposes a process how to secure input data as illustrated in Fig. 4. If the first day for prediction is the D-day, the forecasting data can become an input data recurrently as shown in Fig. 4. The input data is shifted sequentially as the forecast date passes. Finally, input data for seven days after D+8 day is obtained by only the predicted data.

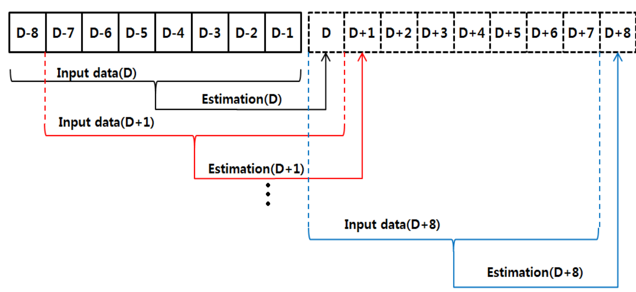


FIGURE 4. Process of input and output data.

C. EXAMPLE: EFFECTIVENESS OF INPUT '1' IN FFNN

In this section, the effectiveness of input '1' in the FFNN is discussed. Assume that the FFNN is designed to identify the function $f(x) = (x-1)^2 + 1$ and there is a single input, x. Because this function has only one variable, x, the FFNN seems to only need x as an input. The FFNN trains the function in the range of x from 0 to 2 with/without input '1' in order to confirm the usefulness of the input '1'. In both cases, the number of hidden neurons is equally three. In other words, two inputs, which are x and 1, are used in the first case and the other case uses only one input, x. After enough iteration, which is ten thousand times, the identifications for both are compared.

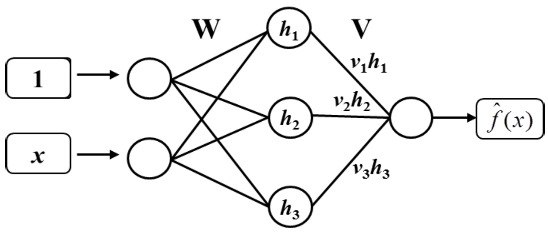


FIGURE 5. FFNN structure for example.

Figure 5 shows the simple structure of the FFNN for the example. Also, since the hidden neurons are three, the identified value can be defined as $\hat{f}(x) = v_1h_1 + v_2h_2 + v_3h_3$, where h_1, h_2, and h_3 are outputs of each hidden neuron and v_1, v_2, and v_3 are weights between hidden and output layers.

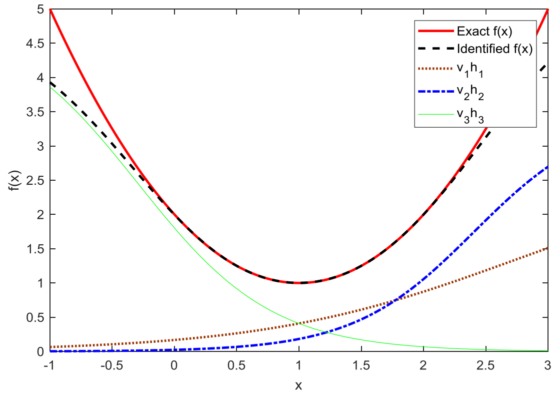


FIGURE 6. Identification result with input 1.

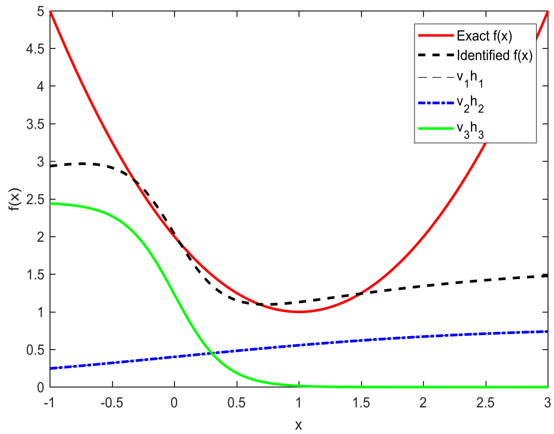


FIGURE 7. Identification result without input 1.

Figure 6 and 7 show the identification results with/without the input '1'. In order to show that the FFNN can be suitable for identification only for the training range, the extended input range from -1 to 3 is entered to the FFNN. In the figures, we can see how the $\hat{f}(x)$ is computed with the sum of the three values v_1h_1, v_2h_2, and v_3h_3. By comparing those figures, we can find the input '1' can help the movement of the reference point of the identified function to train the exact function well.

On the other hand, the two values (v_1h_1 and v_2h_2) have same curves in the second case and v_3h_3 shows different result. In the second case, the FFNN could not train the function at all. Note that this does not prove that the input '1' is absolutely necessary in all cases of training and estimating with the FFNN. However, many researches have used the input '1' to improve training and estimating performances [20]–[25]. Also, when the proposed RANN uses input '1', the training results have improved slightly.

III. CASE STUDIES

In order to verify the performance of the proposed RANN, three case studies are carried out. First, after describing the learning performance, it will be presented that the proposed RANN can estimate the detail patterns of the load for four seasons. By applying to estimate load data for two years, it will also be presented that the proposed RANN is effective for estimating diverse load patterns. Also, despite predicting monthly load, the paper verifies that errors do not increase noticeably.

Then, the performance will be compared with the results of the commercial software (KSLF) used in South Korea. The KSLF has been developed to suit the load forecasting of South Korea and it has been constantly upgraded. The purpose of the KSLF is short-term load forecasting for ten days. Therefore, the forecasting results for ten days are compared for equity.

Finally, the nonlinearity of the load patterns increases in summer season. Especially, the load patterns are very sensitive to temperature changes during tropical night period. At the end of the section, the excellence in learning and predicting the nonlinear patterns during tropical night period is presented.

A. PERFORMANCE OF MID-TERM LOAD FORECASTING

Before discussing the forecasting performance of the proposed RANN, the learning performance will be checked first. Actual load data of South Korea is used for the study. Note that the year corresponding to the load data cannot be specified in the paper. Specifying the year may not be important because the paper focuses on improving and verifying the accuracy for forecasting mid-term loads by the proposed RANN. Therefore, the first year of data used in the paper is defined as D year in the paper.

In general, large data for three or more years is used to let the ANN train load patterns for several years and keep estimation error level low or stable. In some respects, it may seem somewhat insufficient that the proposed RANN trains only one year's load data. However, when the ANN trained load data for many years, the forecasting results became worse. Namely, the results have a tendency to underestimate loads as the training period increases. It is because while temperature changed within a stable range over the years, total annual load of South Korea increased gradually. Therefore, the paper uses one year's data for training and this problem will be briefly discussed at the end of this section.

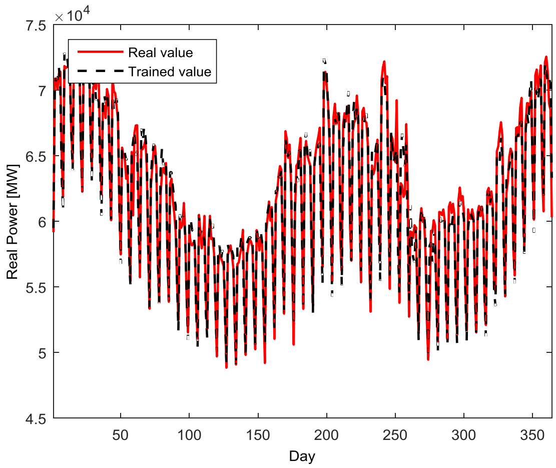


FIGURE 8. Training result for D year by the proposed RANN.

Figure 8 shows the training performance of the proposed RANN. The RANN trains enough load data of D year until the error is converged. In order to measure the error, mean absolute percentage error (MAPE) is calculated. The average MAPE was 1.1% for all training results during two years. It is sufficiently small value to estimate the future load.

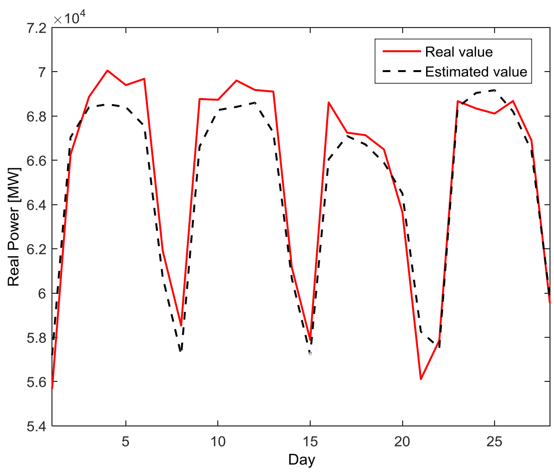


FIGURE 9. Estimation result of power demand for January in D+1 year.

The forecasting performances are illustrated in Figs. 9 to 14. Note that the performances are verified by comparing estimated power loads with the real values for every month of D+1 and D+2 years. Figures representing four seasons during those two years are selected in the paper. Also, the overall analysis of the forecasting error is listed in Table 1. Figures 9 and 10 show the estimation results of power demand for January and February for winter in D+1 year, respectively. As shown in Figs. 9 and 10, the proposed RANN can better predict different pattern characteristics of each week.

Also, Figure 11 and 12 show the estimation results of power demand for May and November in D+1 year, respectively. They correspond to spring and autumn respectively.

Figure 13 and 14 illustrate the estimation results of power demand for March and July in D+2 year, respectively.

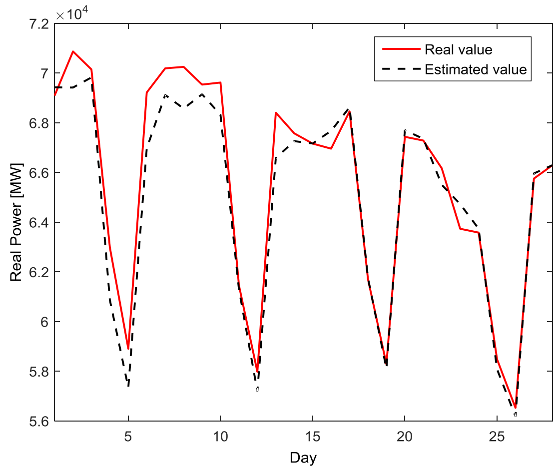


FIGURE 10. Estimation result power demand for February in D+1 year.

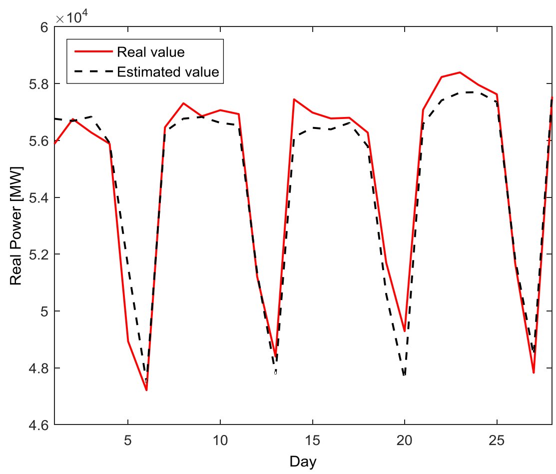


FIGURE 11. Estimation result power demand for May in D+1 year.

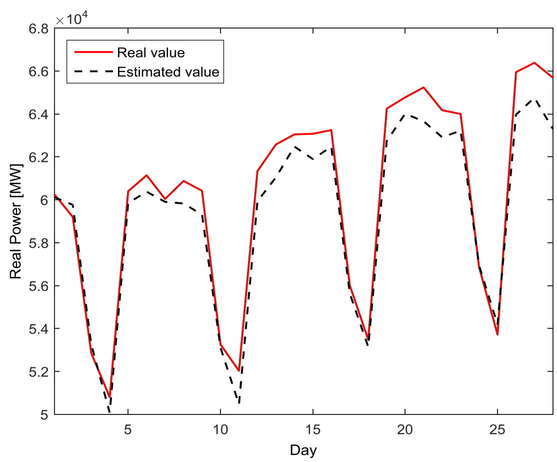


FIGURE 12. Estimation result power demand for November in D+1 year.

They correspond to spring and summer respectively. Based on all the results above, the proposed RANN can predict each week's different pattern accurately even though errors occur in some parts.

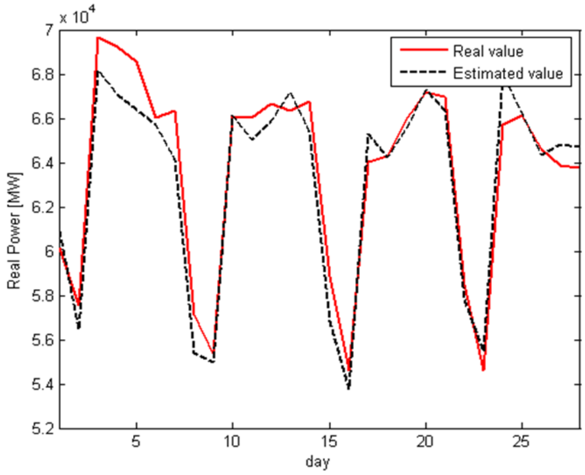


FIGURE 13. Estimation result power demand for March in D+2 year.

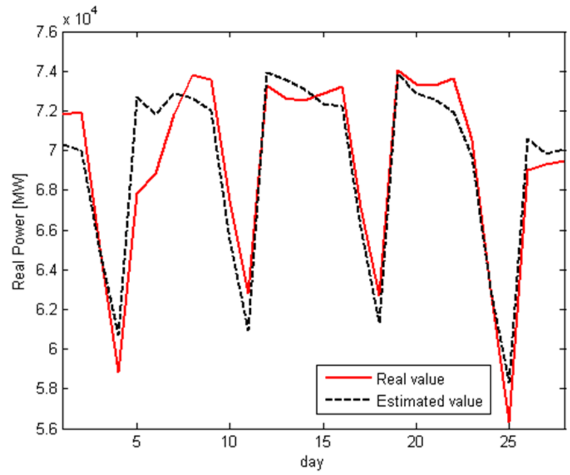


FIGURE 14. Estimation result power demand for July in D+2 year.

TABLE 1. Summary for learning and estimating errors for two years.

Month	D+1 year		D+2 year	
	MAPE in learning	MAPE in estimation	MAPE in learning	MAPE in estimation
Jan.	1.28	1.51	1.19	1.64
Feb.	1.19	1.07	1.18	1.85
Mar.	1.15	1.56	1.19	1.81
Apr.	1.11	1.61	1.21	1.32
May	1.11	1.06	1.18	1.18
Jun.	1.08	1.19	1.15	1.50
Jul.	1.05	2.32	1.16	1.77
Aug.	1.07	2.93	1.18	1.71
Sep.	1.25	1.99	1.3	2.05
Oct.	1.05	1.09	1.2	1.85
Nov.	1.01	1.49	1.22	1.53
Dec.	1.02	2.71	1.01	2.48
Average	1.11	1.71	1.18	1.72

The summary for learning and estimating errors for two years are given in Table 1. Even though the estimating errors are high for some months, overall estimation errors are sufficiently low. Especially, the predictive performances for loads on weekend are excellent when analyzing all simulation results in figures.

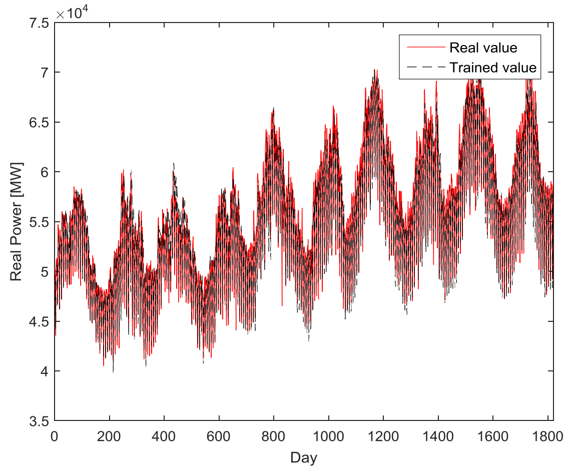


FIGURE 15. Estimation result after training five years' data.

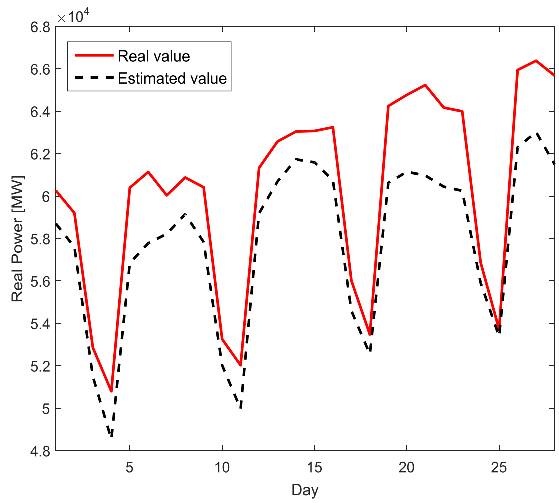


FIGURE 16. Estimation result after training three years' data.

Now, after the proposed RANN trains load data for the past three and five years, it estimates the power demand for November in D+1 year like Fig. 12. Figure 15 shows the training result when five years' load data is trained by the proposed RANN. The training was repeated enough times until the error has converged and the training MAPEs for two cases are 1.53% and 1.81%, respectively, whereas the estimation MAPEs increase as the training year increases. The results are 3.85% and 16.08% and the performances are shown in Figs. 16 and 17. Even though the proposed RANN trains more data and training errors are not seriously large, the performances do not improve. This is because the load demand of South Korea is gradually increased and overall values of learning data is relatively lower than that of present data. As a result, the proposed RANN has a tendency to underestimate the load as the training period increases. Meanwhile, in other country or site having stable or different

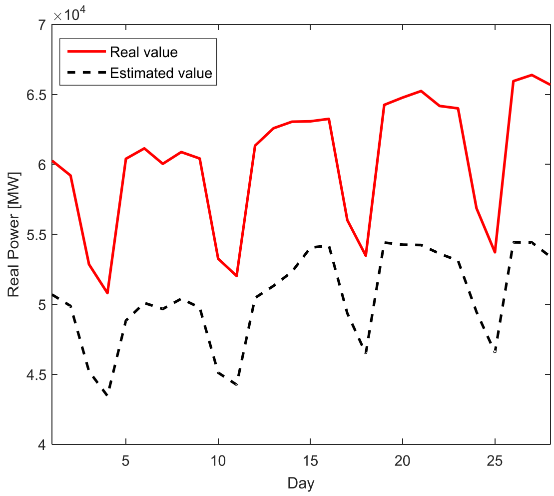


FIGURE 17. Estimation result after training five years' data.

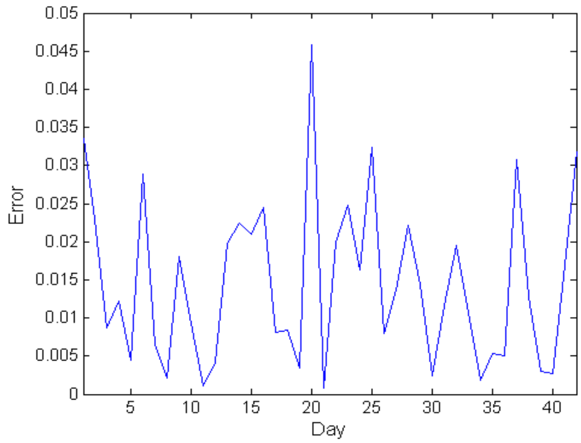


FIGURE 18. Error distribution of estimation for six weeks from January 1st in D+1 year.

load pattern, learning a lot of data with same structure may guarantee better results than this case. However, the key point of the paper is that the paper proposes a new structure of the RANN to forecast mid-term load and the results guarantee the proposed structure is suitable for the mid-term load forecasting even with limited input data.

B. FEATURE OF ERROR ACCUMUATION

As the forecast progresses in the paper, estimated data is continuously calculated and entered back into the input layer for estimating next load. Therefore, errors from the previous estimation process can be accumulated and estimation data can be less accurate as the recurrence process is repeated. In order to prevent this problem, the proposed RANN is designed to learn repetitive patterns better.

Figures 18 and 19 show the error distributions for all estimation data if the proposed algorithm is applied to estimate six weeks' load data. Note that the reason for predicting the load data for two more weeks is to verify whether errors continue to be accumulated and grow. As shown in figures, there is no tendency for error accumulation. Therefore, it is verified that the proposed RANN is suitable for mid-term load forecasting.

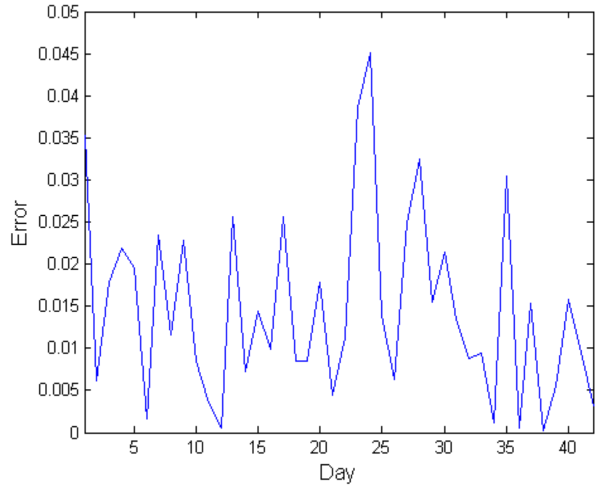


FIGURE 19. Error distribution of estimation for six weeks from March 1st in D+2 year.

C. COMPARSION WITH COMMERCIAL SOFTWARE

In this section, the performances of the proposed RANN are compared with those of commercial software (KSLF), which is used for estimating short-term load of South Korea.

The KSLF is based on exponentially weighted moving average for estimating weekday load and uses temperature sensitivity with N-dimension to be suitable South Korean context [17]. Especially, the weekend loads are forecasted based on fuzzification method of linear regressing analysis. In other words, the KSLF applies appropriate methods on weekdays and weekends respectively.

TABLE 2. Comparison between KSLF and proposed RANN.

Day	MAPE in estimation	
	KSLF	RANN
Weekdays	1.90	1.97
Weekends	2.22	1.57

Therefore, the performances of the KSLF and the proposed RANN are compared on weekdays and weekends separately and the estimation period is limited to ten days. As mentioned before, the KSLF is developed for estimating power demands up to ten days. The MAPEs by applying both methods to power demands in D+2 year are given in Table 2. For weekdays' loads, the MAPE of the proposed RANN is slightly higher but significantly lower for weekend's loads. Even though the proposed RANN is developed for mid-term load forecasting, the performance of the proposed RANN is as excellent as the KSLF.

D. PERFORMANCE OF NONLINEAR LOAD PATTERN FORECASTING

South Korea has four distinct seasons. Therefore, nonlinear characteristics exist in load patterns of South Korea.

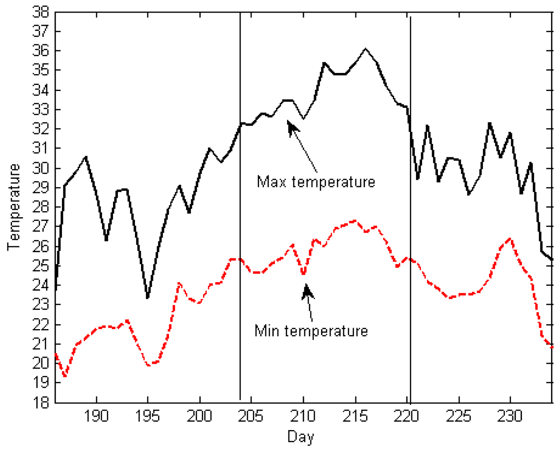


FIGURE 20. Maximum and minimum temperatures during heatwaves in D+1 year.

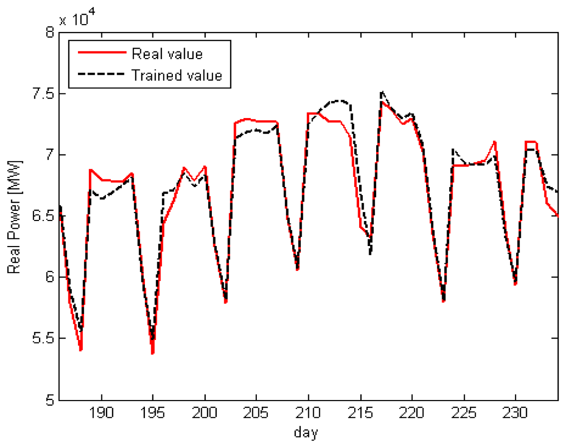


FIGURE 21. Training result for power demand during heat waves.

The nonlinearity becomes especially stronger during heat waves. Heat waves continue for three weeks in D+1 year and the maximum and minimum temperatures in the same period are illustrated in Fig. 20. The actual and forecasting loads for same days with Fig. 20 are shown in Fig. 21. As shown in Fig. 21, the proposed RANN trains the nonlinear load patterns during heat waves accurately. This means that the proposed RANN can estimate exactly same patterns if similar input data is entered.

Actually, in the D+2 year, heat waves occurred in July, which is one month earlier than last year. The heat wave lasted almost three weeks and the power demand suddenly increased. The proposed RANN can estimate suddenly increased loads accurately as shown in Fig. 14.

IV. CONCLUSION

The paper described a method of mid-term daily peak load forecasting using recurrent artificial neural network (RANN). The focus of the paper was to forecast daily peak loads for four weeks with limited input data such as recorded load and temperatures. In general, it is not easy to predict power load up to a month using current load data. The key is to reduce the increase in error as the date to be forecasted moves away from the present day. The input data was selected in order to improve the training and estimating performances and the paper proposed a RANN structure in which the forecasting data was recurrently used as input data.

In order to verify the performance of the proposed method, the proposed RANN was implemented by writing code with MATLAB® software and the three case studies were carried out. First, the proposed RANN was applied to estimate load data for two years. Then, the performance was compared with the results of the commercial software (KSLF) used in South Korea. Finally, the proposed RANN was also applied to estimate the nonlinear load patterns during heat waves. The results of case studies using load data of South Korea verified performances and effectiveness of the proposed RANN.

If other meaningful data (for example, data related to economy or other weather data) can be obtained, the proposed RANN can be designed more precisely. However, the proposed method showed excellent performances even with limited data.

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