A Novel Daily Peak Load Forecasting Method using Analyzable Structured Neural Network

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***Abstract*-- This paper presents a novel daily peak load forecasting method using an analyzable structured neural network in order to explain forecasting reasons. We propose a new training method for the analyzable structured neural network (ASNN) in order to realize accurate daily peak load forecasting and explain forecasting reasons. ASNN consists of two types of hidden units. One type of hidden units has connecting weights between the hidden units and only one group of input units. Another one has connecting weights between the hidden units and all input units. The former type of hidden units allows to explain forecasting reasons. The latter type of hidden units ensures the forecasting performance.**

The effectiveness of the proposed training method is shown applying to daily peak load forecasting. ASNN trained by the proposed new training method can explain forecasting reasons more properly than ASNN trained by the conventional method.

***Index Terms*-- Artificial Neural Network, Peak Load Forecasting, Structural Learning, Knowledge Extraction**

I. INTRODUCTION

Electric load forecasting in power systems is very important task for ensuring reliability and economical operation. Especially, daily peak load forecasting is one of the basic operations of generation scheduling for the next day. An appropriate load forecasting method is expected to forecast accurately and to explain reasons of forecasting results in terms of the importance. Moreover, since accurate forecasting results are required for generation scheduling, the forecasting method has to handle continuous values instead of discretized forecasting values. Therefore, it has to handle continuous values as input and output variables.

Many statistical methods have been conventionally used for such forecasting. Usually, a linear regression model has been practically used in a central load-dispatching center. An operator is able to understand the reason and relations of forecasting results using the linear regression model. However, it is difficult to obtain the accurate forecasting results because the model is constructed by linear functions. Moreover, it has been difficult to construct a proper nonlinear regression model using nonlinear functions and to investigate complex correlations between electric load and input variables such as weather conditions, seasonal factors, and difference between weekdays and weekends.

Recently, a number of artificial neural network (ANN) approaches for electric load forecasting have been proposed [1-9]. In these studies, ANN techniques have been used to forecast the daily peak load, daily load curve and so on. The ANN is regarded as a powerful method for handling nonlinear complex phenomenon, and it is able to develop a forecasting model automatically only by training with stored actual data. However, the structure of trained ANN is said to be a *black box*. Namely, the operator cannot obtain the reason of forecasting results such as independent relations between each input factor and output factor using the conventional ANN.

Recently, many studies have been done to develop a method for explanation of the reason of output by neural networks. For example, structural learning methods for ANN [10][11] and an analyzable structured neural network (ASNN) [14][15] have been proposed. The structural learning methods for ANN are developed for the problem with discrete value and cannot be applied to the problem with continuous value such as electric load forecasting. The ASNN can handle continuous values as input and output variables. However, the ASNN trained by conventional algorithm [14][15] cannot always extract proper knowledge from the actual data.

This paper proposes a new training method for ASNN and a novel daily peak load forecasting method using ASNN. ASNN trained by the proposed training method can extract proper knowledge and explain the reasons of forecasting results with independent correlation between input variables and peak load.

The effectiveness of the proposed method is shown by a comparison between actual correlation and extracted correlation from the trained neural network. Finally, forecasting performances using the proposed method are verified by a comparison with forecasting results using conventional ANN trained by the back propagation.

II. ANALYZABLE STRUCTURED NEURAL NETWORK

Fig. 1 shows structure of the ASNN, which has some network modules. The network module consists of two types of hidden units. One type of hidden units has connecting weights between only one group of related input units. The network module with this type of hidden units is called a *sparse-connecting module*. Another one has connecting weights between all input units. The network module with this type of hidden units is called an *all-connecting module*. The former type of hidden units allows to analyze each relation

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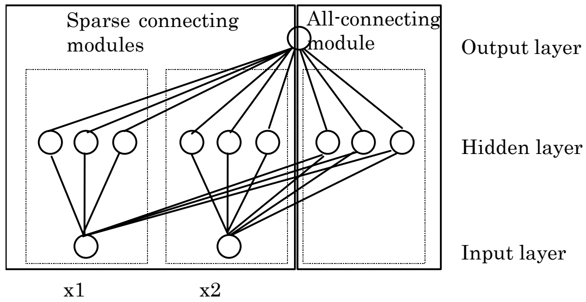

Fig. 1. Structure of the proposed neural network.

between a certain input data and a corresponding output data. The latter type of hidden units ensure the performance of the neural network as same as the conventional ANN.

It is very important for ASNN that sparse-connecting modules must present only independent correlation between only one group of input units and output unit, and all-connecting module must present only interaction between input units in order to extract correlation from training data and explain forecasting reasons. However, the conventional training method cannot always extract proper knowledge from the actual data and train ASNN, because both types of connecting module are trained at the same time. The proposed new training method improves the disadvantage of the conventional training method of ASNN. Each connecting module is trained independently. Those details are shown as following section.

III. TRAINING METHOD FOR ASNN

A. Formulation of Training Algorithm

If a trained neural network includes useless hidden units and useless connections, knowledge extraction from the trained neural network is difficult, and the neural network has low generalization ability. The proposed ASNN is trained using a structural learning algorithm with superposed energy function (SLSEF) [12] and a structural learning algorithm with forgetting (SLF) [10] for easy analysis and high generalization ability.

In order to use the SLSEF, some sub-perceptrons have to be defined. Connections of small number of sub-perceptrons are grown up early, and connections of large number of sub-perceptrons are grown up slowly. Therefore, the growth of useless hidden units is controlled, and the emergence of distributed representations on hidden layers is controlled as well. The SLF removes useless connections using the model complexity penalty term in the energy function. The proposed energy function which used SLSEF and SLF algorithms concurrently is as shown by:

$$F = \sum_{i}^{H} \beta_i E_i + \varepsilon' \sum \left| w_{ij} \right| \tag{1}$$

$$E_i = \frac{1}{2}\left(y_t - y_i\right)^2 \tag{2}$$

where, H : total number of sub-perceptron,
β i : weighting factor of sub-perceptron,
ε' : forgetting factor,
wij : connecting weight,
yt : training data,
yi : output of sub-perceptron i.

The connecting weights are changed by the following equation:

$$\Delta w_{ij} = -\eta \frac{\partial F}{\partial w_{ij}} = \Delta w'_{ij} - \varepsilon \,\mathrm{sgn}(w_{ij})$$
$$\mathrm{sgn}(x) = \begin{cases} -1 & (x < 0) \\ 0 & (x = 0) \\ 1 & (x > 0) \end{cases} \tag{3}$$

where, Δwij' : weight correction using only SLSEF,
ε : forgetting factor.

B. Training Method for ASNN

The proposed new training method is consisted of the following three steps. Fig. 2 shows samples of each training step for ASNN that forecasts daily peak load.

Fig. 2 (a) shows the initial structure of the ASNN before training. The ASNN consists of three sparse-connecting modules and one all-connecting module. Each spars-connecting module can have one input group included several input units.

Step 1 is shown by Fig.2 (b). Each sub-perceptrons is trained independently. A purpose of this step is to realize certain training of independent relation between one input group and output. Most useless hidden units are pruned through step 1.

Step 2 is shown by Fig.2 (c). All sparse-connecting modules are merged and trained again using the connecting weights trained at step 1 as initial connecting weights of step 2. At this step, the neural network can study independent relation between input factors and the output. However, the neural network cannot study interactions between input factors.

Step 3 is shown by Fig.2 (d). A purpose of this step is that all-connecting module studies interactions among input factors. All-connecting module is merged into trained sparse-connecting modules. For pruning useless hidden units of all-connecting module, special sub-perceptrons are defined. The sub-perceptron 1 consists of hidden units of all of sparse-connecting modules (all group) and one hidden unit of all-connecting module. The sub-perceptron 2 consists of the sub-perceptron 1 and one more hidden unit of all-connecting module. Other sub-perceptron also consists of the lowly numbered sub-perceptrons and one more hidden units of all-connecting module as shown in fig.2 (d). Hidden units included in lowly numbered sub-perceptrons grow up early, and hidden units included in highly numbered sub-perceptrons grow up slowly. All of hidden units have the same forgetting speed. Therefore, hidden units in lowly numbered sub-perceptrons have tendency to grow, while those in highly numbered sub-perceptrons have tendency to forget. Thus, useless hidden units of all-connecting module are pruned automatically.

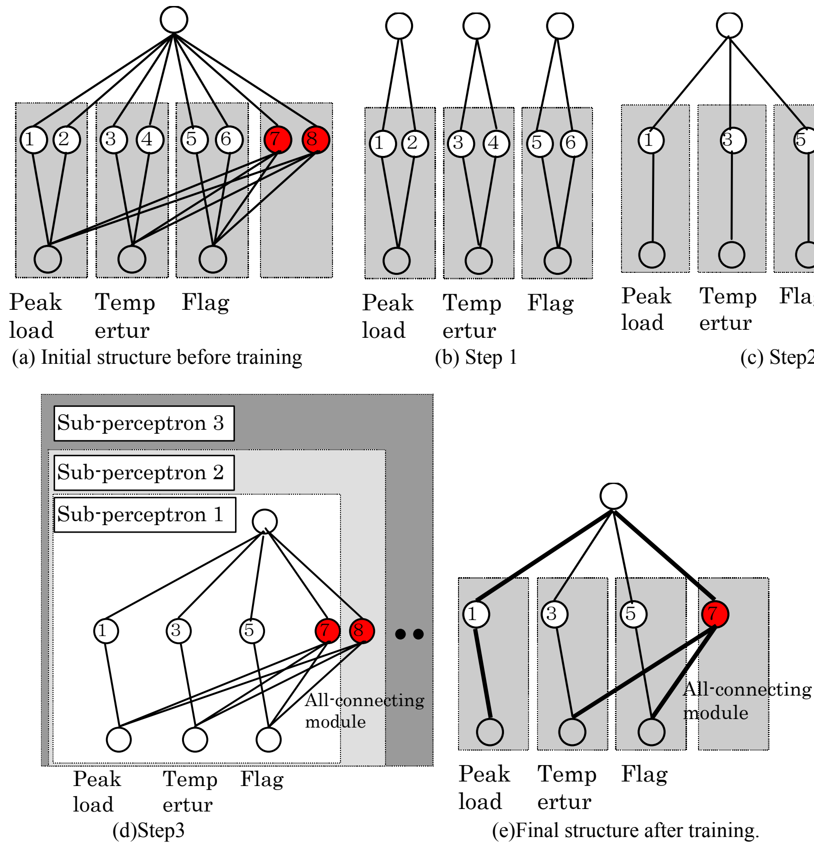

Fig.2. Each training step of the proposed training method for ASNN.

Fig. 2 (e) shows the final structure of ASNN after training. Sparse-connecting modules studied only easy independent relations between input factors and output, and all-connecting modules studied only complicated interactions between input factors.

IV. Peak Load Forecasting Using ASNN

The following framework is developed for the peak load forecasting using the ASNN:

Step.1 Selection of input variables

A set of the input variables that are significantly correlated with the output variable is selected from available data.

For example, the following data are selected:

- Actual peak load,
- Weather conditions such as maximum temperature, minimum temperature, and humidity,
- The information to identify weekday, Saturday, Sunday, and holiday

Step.2 Grouping of input variables

The independent correlation between a group of input variables and output variables can be extracted from ASNN at step. 4. Therefore, An operator divides the input variables into some groups for various analysis purposes at this step. Each group is corresponding to the sparse-connecting module of ASNN.

For example, the following groups can be constructed for weather conditions:

- A group for all input variables about weather conditions,
- A group for maximum temperature and that for minimum temperature,
- A group for the temperature of the target day and that for the preceding day.

Step.3 Training ASNN

The structure of ASNN is initialized using the results of Step 1 and Step 2, and ASNN is trained. The optimized structure of neural network is obtained through the above-mentioned training algorithm. Namely, the independent relations between a group of input and output unit are constructed in the ASNN.

Step.4 Analysis and knowledge extraction from ASNN

The relations between each group of input variables and the output variable are extracted from the trained ASNN. For example, the independent relation between temperature and peak load are obtained. If several ASNNs are trained, different

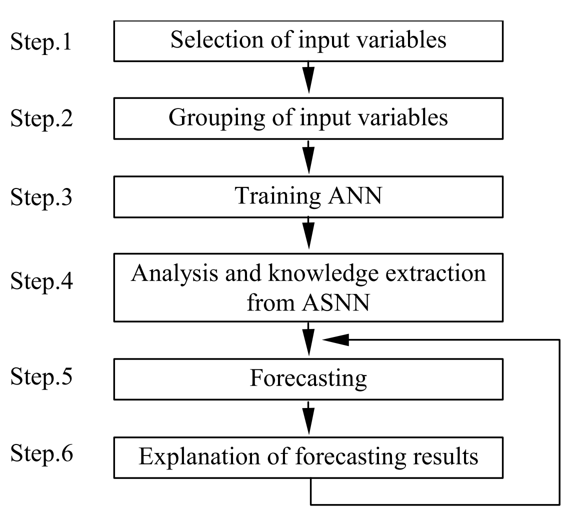

Fig. 3. A general flow chart of the proposed method

correlation can be obtained from each ASNN. Therefore, operators can select an appropriate forecasting model, which fits their experienced knowledge. This is one of the advantages of ASNN.

Step.5 Forecasting

The forecasting results are obtained using the trained ASNN.

Step.6 Explanation of forecasting results

The trained ASNN has the hidden units that are connected with only one input group. Therefore, ratios of input values from each group to the output neuron can be calculated. Influence degree of each input group to the output can be explained using the ratios.

Fig.3 shows a general flow chart of the proposed method.

V. NUMERICAL EXAMPLES

A. *Simulation Conditions*

ASNNs trained by the proposed method and the conventional method, and the conventional ANN trained by the back propagation are applied to daily peak load forecasting for the next day. ASNNs and ANN are constructed for each season and are trained using actual data for three years. Input variables are referred to the example of practical applications [8][9]. Table. 1 shows the input variables.

The ASNN input variables are divided into the following three groups:

- A group for all input variables about the temperature,
- A group for all input variables about the previous load,
- A group for all input variables about the flag data.

1) Case 1 (spring)

ASNNs trained by the proposed method and a conventional ANN trained by the back propagation are applied to spring period, which is consisted of April and May. The purposes of case 1 are comparison of forecasting performances of ASNN trained by the proposed method and the conventional ANN, and comparison of extracting performance of correlation using the proposed training method and the conventional training method.

Fig. 4 and Fig.5 show major characteristics of spring season. Fig.4 shows actual correlations between temperature and target peak load in spring period. Both positive and negative correlations are observed. Fig.5 shows actual correlations between previous peak load and target peak load. Only positive correlation about peak load is observed.

2) Case 2 (summer)

The proposed ASNN method and the conventional ANN method are applied to summer period, which is consisted of June and July. Fig. 6 and Fig.7 show major characteristics of summer season. Fig.6 shows actual correlations between temperature and target peak load in summer period. Fig.7 shows actual correlations between previous peak load and target peak load. An only positive correlation about temperature is observed differently from spring.

TABLE I
INPUT VARIABLES.

Input group	Case1 (spring)	Case 2 (summer)
Previous load	Peak load (i - 1) Peak load (i - 7)	
Temperature	Max. temperature (i) - (i - 2) Min. temperature (i) - (i - 2)	Max. temperature (i) - (i - 7) Min. temperature (i) - (i - 7)
Flag data	Saturday flag (i) - (i - 2) Sunday and holiday flag (i) - (i - 2)	

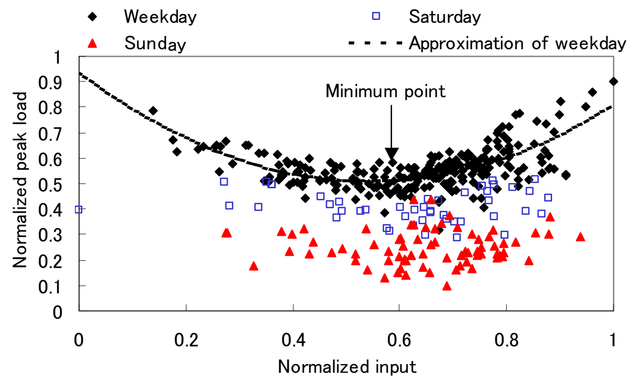

Fig.4. Actual correlation between temperature and target peak load during spring period.

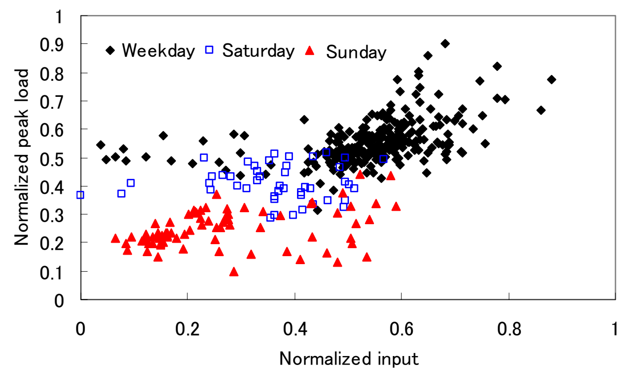

Fig.5. Actual correlation between target peak load and previous peak load seven days before the target day during spring period.

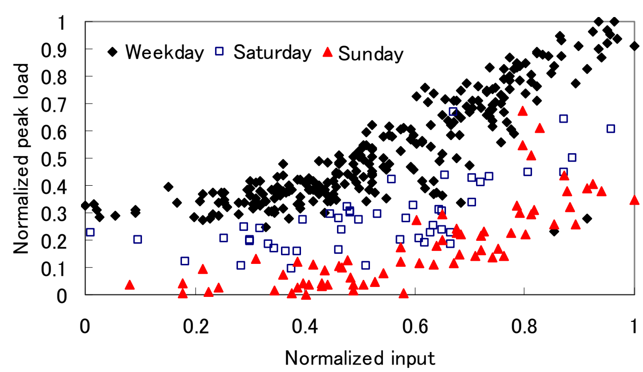

Fig.6. Actual correlation between temperature and target peak load during summer period.

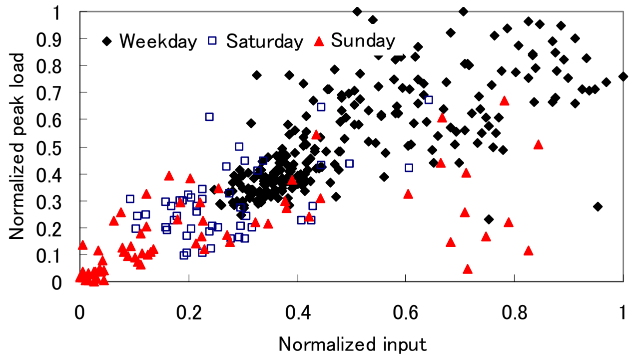

Fig.7. Actual correlation between target peak load and previous peak load seven days before the target day during summer period.

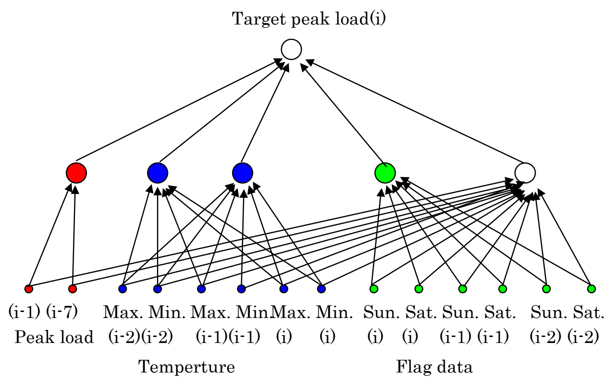

Fig.8 Structure of trained ASNN for spring period.

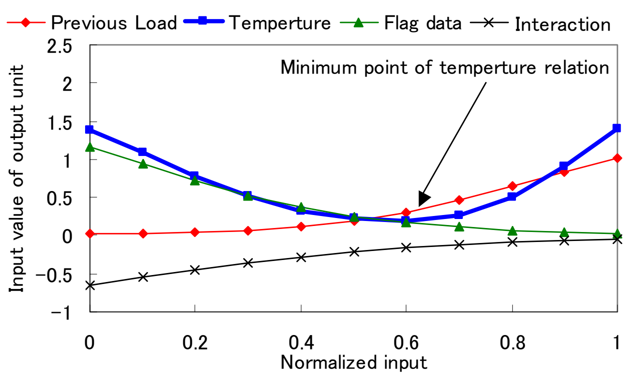

Fig.9 Extracted correlation between input groups and peak load during spring period trained by proposed method.

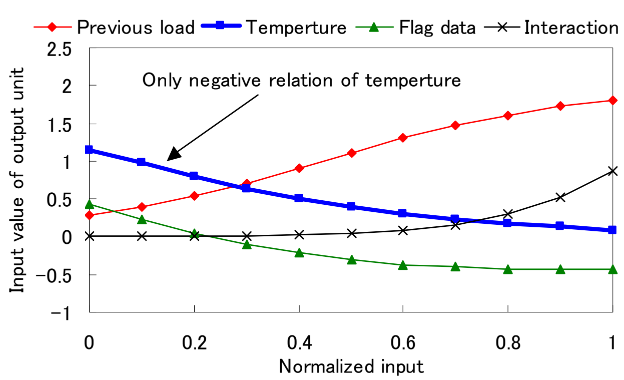

Fig.10 Extracted correlation between input groups and peak load during spring period trained by conventional method

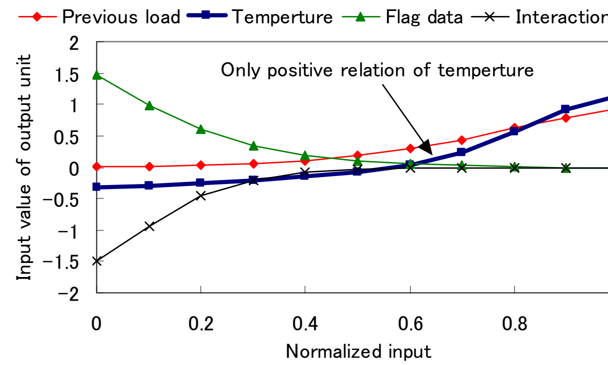

Fig11. Extracted correlation between input groups and peak load during summer period trained by proposed method.

TABLE II
FORECASTING RESULTS (MAPE).

	Spring	Summer
Conventional ANN trained by the back propagation	2.66%	1.64%
ASNN trained by the conventional method	2.39%	1.60%
ASNN trained by the proposed method	2.53%	1.57%

MAPE: Mean absolute percent error

B. Simulation Results

1) Case 1 (spring)

ASNN before training have three sparse-connecting modules and one all-connecting module. Each connecting module consists of two hidden units. Fig. 8 shows the structure of ASNN after training for spring period by the proposed new training method. The sparse-connecting module for the peak load has one hidden unit. That for the temperature have two hidden units, and that for the flag data have one unit after training. The all-connecting module has one hidden unit after training.

It is observed that the correlation between the temperature and the target peak load indicates a quadric relation as shown in Fig. 4. This means the peak load consists of cooling load and heating load in spring period. Fig. 9 shows the extracted correlation from ASNN trained by the proposed method. The extracted correlation between the temperature and the target peak load indicates the same characteristics of the actual correlation as shown in Fig. 4. The inflection points of the extracted and the actual correlation indicate 0.6 as normalized temperature value. The extracted correlation between the target peak load and previous peak load also indicates the same characteristic of the actual correlation as shown in Fig.5. It can be observed in Fig. 4 that sets of peak loads of weekday, Saturday, and Sunday are decreased gradually. The extracted correlation between flag data and peak load is decreased from 0 to 1 as shown in Fig. 9. Namely, the extracted correlation indicates the same characteristic of actual correlation.

Fig.10 shows extracted correlation from ASNN trained by the conventional training method. Only positive correlation between the temperature and the target peak load is observed, which is different from the characteristic as shown in Fig.4. The ASNN trained by the conventional trained method cannot always extract proper correlations, because all-connecting module sometimes presents independent relations that must be presented by sparse-connecting modules.

2) Case 2 (summer)

The major characteristic of summer is different from that of spring. Only positive correlation about the temperature is observed as shown in Fig. 6. The correlations about peak load and flag data are the same as spring. The extracted correlations indicate the same characteristics of the actual correlations as shown in Fig. 6 and Fig. 11.

Table 2 shows the comparison of forecasting errors using ASNN and the conventional ANN trained by the back propagation. ASNN trained by the proposed method can forecast accurately compared with the conventional ANN method.

The conventional ANN cannot explain forecasting reasons and extract correlation between input and output factor as shown before. ASNN trained by the proposed new training method can explain the forecasting reasons more properly than the conventional training method. Moreover, the proposed ASNN method can forecast more accurately than the conventional ANN method

VI. Conclusions

This paper proposes a new training method for an analyzable structured neural network and a novel daily peak load forecasting method using the analyzable structured neural network. The results of the paper can be summarized as follows:

(1) The new training method for the analyzable structured neural network is proposed. ASNN trained by the proposed method can extract correlation between input and output factor more properly than ASNN trained by the conventional training method.

(2) The results of the numerical simulation indicate that the proposed method can provide power system operator with the reason of forecasting results. Moreover, it can forecast the daily peak load more accurately than the conventional ANN method trained by the back propagation.

This paper only presents application of the analyzable structured neural network to daily peak load forecasting. However, the explanation function of the analyzable structured neural network is generally utilized in various applications. Development of explanation functions of the neural network for various applications is one of the future works.

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