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PEAK LOAD FORECASTING USING ANALYZABLE STRUCTURED NEURAL NETWORK

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Abstract: This paper presents daily peak load forecasting using an analyzable structured neural network. Recently, a number of neural network approaches for peak load forecasting have been proposed. The purpose of these studies is to construct a nonlinear model for accurate forecasting using multilayer neural networks. However, conventional multilayer neural networks are said to be a black box. Namely, it is difficult to explain reasons of forecasting results. The proposed neural network has hidden units with connecting weights between only one group of related input units. This feature allows to analyze independent relations between input and output units. The effectiveness of the proposed method is shown by a comparison with actual and extracted correlation from the trained neural network.

Keywords: Peak Load Forecasting, Artificial Neural Network, Structural Learning, Knowledge Extraction

I. INTRODUCTION

Electric load forecasting in power systems is very important task for insuring reliability and economical operation. Especially, daily peak load forecasting is one of the basic operations of generation scheduling for the following day. An appropriate load forecasting method is expected to forecast accurately and to explain reasons of forecasting results in terms of the importance. Moreover, it have 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 relevance 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 correlation 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. In these studies, ANN techniques have been used to forecast the daily peak load, daily load curve and so on [1-9]. 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 a correlation coefficient between each input factor and output factor.

Recently, many studies to explain the reason of output using nonlinear functional model have been proposed. For example, structural learning methods for ANN [10][11] and optimization methods for fuzzy inference models [12][13] are proposed. The ANN structural learning methods are developed for the problem with discrete value and cannot be applied to the problem with continuous value such as electric load forecasting. The optimization methods for fuzzy inference model are applied for the problem with discrete value and for the problem with continuous value. Fuzzy rules for forecasting are obtained using these fuzzy optimization methods. However, the intelligible fuzzy rules cannot be obtained necessarily in the case of using many input factors. Namely, the appropriate load forecasting method with high forecasting accuracy, explainable ability, and handling of continuous values has not been proposed yet.

This paper proposes a daily peak load forecasting method using an analyzable structured neural network (ASNN). The proposed method can explain the reasons of forecasting results with independent correlation between input variables and peak load extracted from the ASNN. The method can forecast accurately with nonlinear forecasting model. Moreover, the ASNN can handle continuous values as input and output variables.

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

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

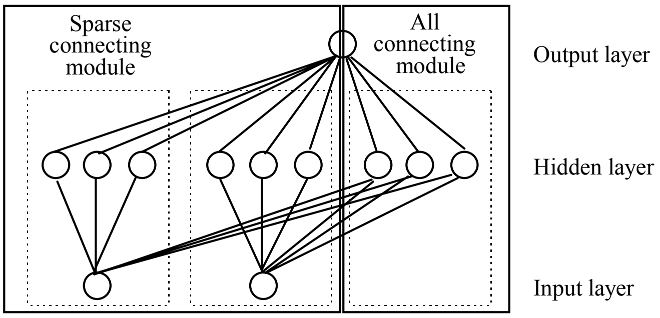


Fig. 1. Structure of the proposed neural network.

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

III. TRAINING METHOD FOR ASNN

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 by a structural learning algorithm with superposed energy function (SLSEF) [14] 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,

w_{ij} : connecting weight,

y_t : training data,

y_i : output of sub-perceptron i.

The connecting weights are changed by 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, $\Delta w_{ij}'$: weight correction using only SLSEF,

ε : forgetting factor.

Training Method for ASNN

The proposed ASNN is trained by the following three steps. Fig. 2 shows each training step for ASNN.

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 type of modules is allocated alternately. A purpose of this step is decision of rough structure for training data. Most useless hidden units and connections are pruned through step 1.

Step 2 is shown by Fig. 2 (c). A purpose of this training step is increase of connecting weight values of sparse-connecting modules. Sub-perceptron 1 consists of the all sparse-connecting modules and sub-perceptron 2 consists of the all-connecting module. Training of the sub-perceptron 1 is accelerated compared with that of the sub-perceptron 2 through step 2. Namely, the independent relations between an input and output unit are constructed especially for sparse-connecting module in the ASNN.

Finally, the trained ASNN is obtained by step 3 in Fig. 2 (d) and Fig. 2 (e). This step is carried out for optimization of the ASNN. Hidden units are re-allocated according to the following goodness factor, which presents an importance of hidden units [15]. Namely, a hidden unit with the largest goodness factor value is allocated to sub-perceptron 1.

$$G_i = \sum_{i}^{P} (w_i O_i)^2 \tag{4}$$

where, G_i : goodness factor of hidden unit i,

O_i : output value of hidden unit i,

P : total number of training patterns.

IV. PEAK LOAD FORECASTING USING ASNN

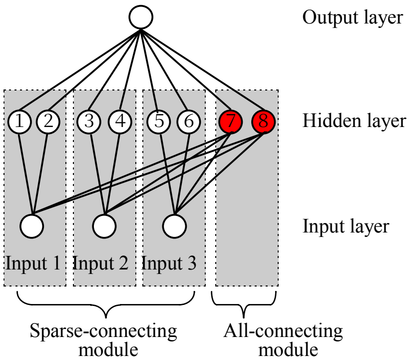
The following framework is developed for the peak load forecasting using ASNN:

Step.1 Selection of input variables

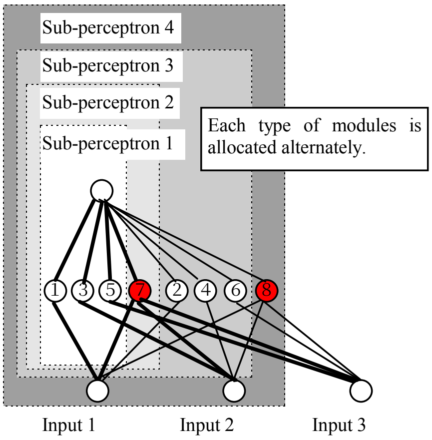
A set of the input variables that are significantly correlated with the output variable is selected from available data.

For example, the following data are selected:

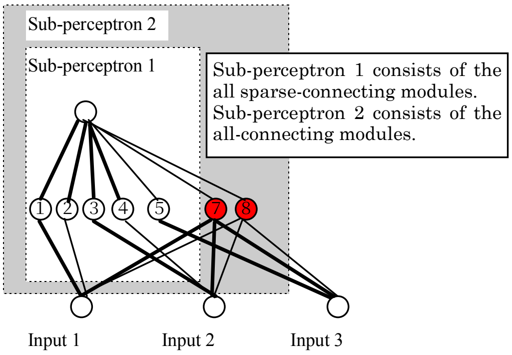
- Actual peak load,
- Weather conditions such as maximum temperature, minimum temperature, and humidity,
- The information to identify weekday, Saturday, Sunday,



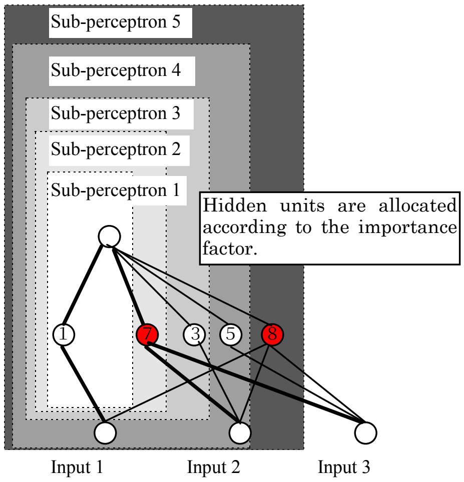
(a) Initial structure before training



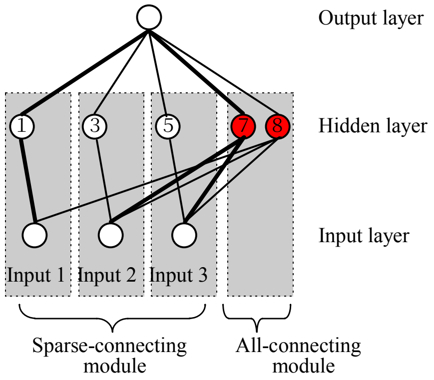
(b) Step 1 (decision of rough structure)



(c) Step 2 (increase of weight values of sparse-connecting module)



(d) Step 3 (optimization of the ASNN)



(e) Final structure after training

Fig. 2. Each training step by ASNN.

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 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 advantage of ASNN.

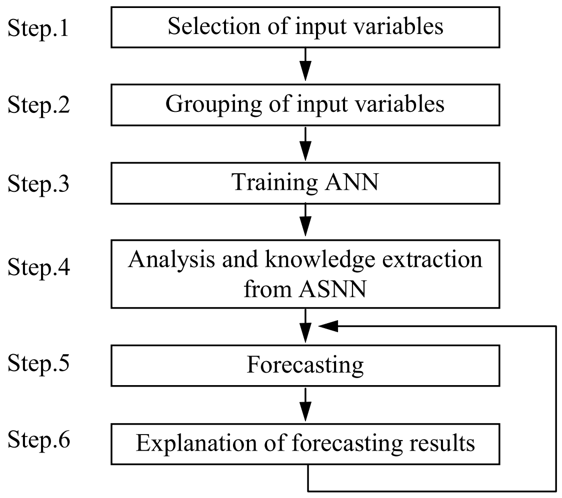


Fig. 3. A general flow chart of the proposed method.

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. Degree of influence to each input group can be explained using the ratios.

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

V. NUMERICAL EXAMPLES

Simulation Conditions

The proposed ASNN method and a conventional ANN method are applied to daily peak load forecasting for the following day. The ASNN and the 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.

The capability of ASNN is verified with the following test cases those have different characteristics.

(1) Case 1

The proposed ASNN method and the conventional ANN method are applied to spring period, which is consisted of April and May. Fig. 4 shows a major characteristic of case 1. It shows an actual correlation between temperature and peak load in spring period. Both a positive and a negative correlation are observed.

Table 1. 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)	

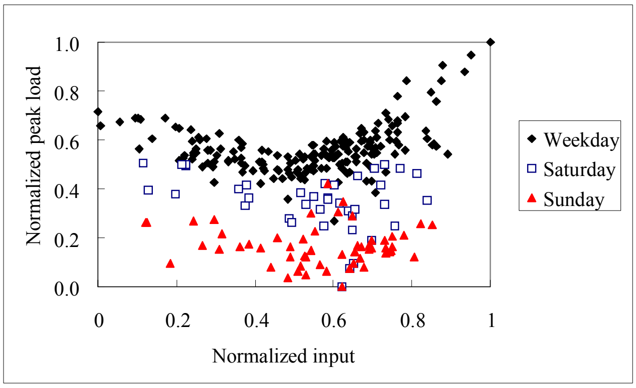


Fig. 4. Actual correlation between temperature and peak load during spring period (case 1).

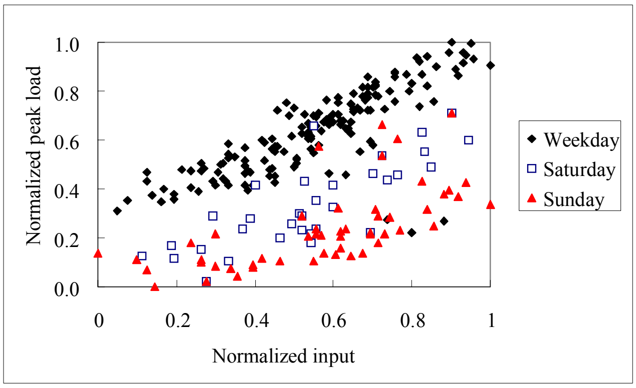


Fig. 5. Actual correlation between temperature and peak load during summer period (case 2).

(2) Case 2

The proposed method and the conventional ANN method are applied to summer period, which is consisted of only August. Fig. 5 shows the major characteristic of case 2. It shows an actual correlation between temperature and peak load in summer period. An only positive correlation is observed differently from case 1. It is especially important to forecast accurately because peak load increases greatly in summer period.

Simulation Results

(1) Case 1

The ASNNs before training have three sparse-connecting modules and one all-connecting module. Each connecting module consists of three hidden units. Fig. 8 shows the structure of the ASNN after training for spring period. 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 two units after training. The all-connecting module has one hidden units after training.

It is observed that the correlation between the temperature and the 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. 6 shows the extracted correlation from the trained ASNN. The extracted correlation between the temperature and the 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 0.5 as normalized temperature value. 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. 6. Namely, the extracted correlation indicates the same characteristic of actual correlation. It is also observed in Fig. 6 that the extracted correlation between the previous load and the peak load indicates an approximate linear relation. Since the peak load increases day by day in spring period, the correlation trained by ASNN must be correct. The input value of output unit for interaction factor indicates approximate constant value, and roll of the all-connecting module seems to be adjustment for accurate forecasting.

Table 2 shows the comparison of forecasting errors using the proposed ASNN method and the conventional ANN method. The MAPE of forecasting errors is 2.28 % using the proposed ASNN method. The proposed method can forecast accurately compared with the conventional ANN method.

(2) Case 2

The major characteristic of case 2 is different from that of case 1. A positive correlation between the temperature and the peak load are observed as shown in Fig. 5. The same correlation is observed in Fig. 7. The correlation about flag data is the same as case 1. The correlation between the previous load and the peak load are not observed. The temperature and flag data affect greatly the peak load without the previous load in the summer period.

Table 2 shows the forecasting errors using the conventional ANN method and the proposed ASNN method. The MAPE of forecasting errors is 2.46 % using the proposed ASNN method. This method can forecast accurately compared with the conventional ANN method.

Above-mentioned analysis cannot be obtained using the conventional ANN method. The proposed ASNN method can explain the reason of forecasting results, which fits the operator's experienced knowledge. Moreover, the proposed ASNN method can forecast more accurately than the conventional ANN method.

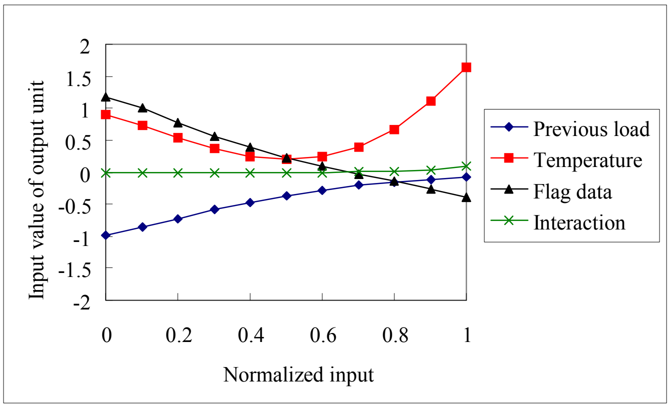


Fig. 6. Extracted correlation between input groups and peak load during spring period (case 1).

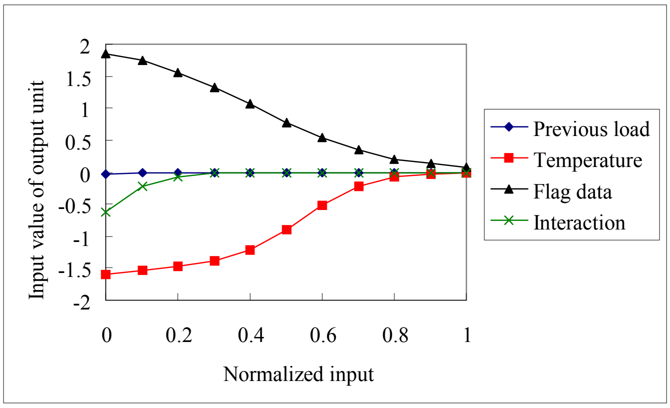


Fig. 7. Extracted correlation between input groups and peak load during summer period (case 2).

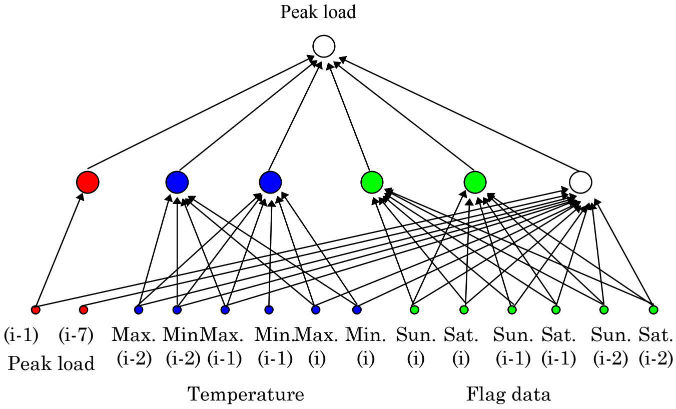


Fig. 8. Structure of trained ASNN for case 1.

Table 2. Forecasting results (MAPE).

	Case1 (spring)	Case 2 (summer)
Conventional ANN	2.64 %	2.73 %
Proposed ASNN	2.28 %	2.46 %

MAPE : Mean absolute percent error

VI. CONCLUSIONS

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

(1) The analyzable structured neural network that can be extracted independent relations between input and output units have been developed.

(2) The proposed method can construct the appropriate forecasting model automatically considering the difference between input and output factor.

(3) The results of the numerical simulations 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.

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