Combined Extension Neural Network and Multi-Regression Analysis Method for Yearly Load Forecasting

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Summary
In this paper, forecasting models of yearly peak load and electricity demand are built according to the gross domestic product (GDP) and economic growth rates. First, a novel clustering method based on the extension neural network is introduced to recognize the load types of yearly peak load (YPL) and yearly electricity demand (YED). Second, according to the load data of every load type, we use the multi-regression analysis method (MRAM) to build the load forecasting models of every load type, and then the forecasting models can be used to forecast the values of YPL and YED at the forecasting time. To verify the proposed forecasting method, the statistics of YPL and YED in Taiwan have been tested. The compared forecasting results with the grey GM (1,1) model show that the proposed method has better accuracy for both YPL and YED forecasting.

Key words: yearly peak load, yearly electricity demand, ENN, multi-regression analysis method, grey model.

Introduction
Yearly load forecasting is one of the most important subjects for plan and operation in power systems. The amount of power load in a country is an index of national economics and progress. In general, the more civilization the more power is required in a country, comparing the economic growth and the electricity demand growth in Taiwan shows this result after B. C.1997 [1]. So, correct power load forecasting is one of the most important techniques in a progressing country. According to statistical data, the higher GDP of a country, the higher electricity demand for each person.

Various models for load forecasting have been reported in the literature, there are including statistical methods [2, 3], the expert system [4], neural networks (NN) [5, 6], and grey theory [7, 8]. Artificial neural networks are currently established as a promising approach to load forecasting since they are able to learn the functional relationship between system inputs and outputs through a training process. However, a limitation of the neural network (NN) approach is difficult to understand the content of network memory, and the neural network approaches need large amounts of training data, and thus require heavy computational efforts to create satisfactory models. Grey forecasting models do not need large amounts of data. They have been successfully applied in YPL forecasting [8], but the accuracy of grey forecasting models still needs further improvement. This paper proposed a novel forecasting method; we use a new neural network topology, called the extension neural network that was proposed in our recent paper [9-11], to recognize the load types of yearly peak load (YPL) and yearly electricity demand (YED). Then, according to the load data of every load type, we use the multi-regression analysis method (MRAM) to build the load forecasting models of every load type.

2. Extension neural network
The schematic structure of the ENN is depicted in Fig. 1, there are two connection values (weights) between input nodes and output nodes; one connection represents the lower bound, and the other connection represents the upper bound for this classical domain of the features. The connections between the \( j \)-th input node and the \( k \)-th output node are \( w_{kj}^L \) and \( w_{kj}^U \). This image is further enhanced in the process characterized by the output layer. The output layer is a competitive layer. There is one node in the output layer for each prototype pattern, and only one output node with nonzero output to indicate the prototype pattern that is closest to the input vector.

Fig. 1. The structure of extension neural network (ENN).
2.1 Learning algorithm of the ENN

The learning of the ENN can be seen as supervised learning, before the learning, several variables have to be defined. Let training set \( \{X_1, T_1\}, \{X_2, T_2\}, \ldots, \{X_Q, T_Q\} \), where \( Q \) is the total number of training patterns, \( X_i \) is an input vector to the neural network and \( T_i \) is the corresponding target output. The \( i \)-th input vector is \( X_i = [x_{i1}, x_{i2}, \ldots, x_{in}] \), where \( n \) is the total number of the features. To evaluate the learning performance, the error function is defined below:

\[
E_i = \frac{1}{2} \sum_{j=1}^{n} (t_{ij} - o_{ij})^2
\]

Where \( t_{ij} \) represents the desired j-th output for the i-th input pattern, \( o_{ij} \) represents the actual j-th output for the i-th input pattern. The detailed supervised learning algorithm can be described as follows:

**Step 1:** Set the connection weights between input nodes and output nodes according to the range of classical domains. The range of classical domains can be directly obtained from previous experience, or determined from training data as follows:

\[
w_{ij}^L = \min \left\{ v_{ij} \right\} ; \quad w_{ij}^U = \max \left\{ v_{ij} \right\}
\]

for \( i=1, 2, \ldots, Q; \quad j=1, 2, n; \quad k=1, 2, \ldots, n_c \)

**Step 2:** Read the i-th training pattern and its cluster number \( p \)

\[
X_i = [x_{i1}, x_{i2}, \ldots, x_{in}]
\]

(3)

**Step 3:** Use the extension distance (ED) to calculate the distance between the input pattern \( X_i \) and the \( k \)-th cluster as follows:

\[
ED_{ik} = \sum_{j=1}^{n} \left( x_{ij} - \frac{(w_{ij}^U + w_{ij}^L)}{2} \right) \left( \frac{(w_{ij}^U - w_{ij}^L)}{2} \right)
\]

for \( k=1, 2, \ldots, n_c \)

(4)

**Step 4:** Find the \( m \), such that \( ED_{im} = \min \{ED_{ik}\} \). If \( m = p \) then go to Step 6; otherwise Step 5.

**Step 5:** Update the weights of the \( p \)-th and the \( m \)-th clusters as follows:

\[
\begin{align*}
L_{ij}^{new} &= L_{ij}^{old} + \eta(x_{ij} - \frac{w_{ij}^{U(old)} + w_{ij}^{L(old)}}{2}) \\
U_{ij}^{new} &= U_{ij}^{old} + \eta(x_{ij} - \frac{w_{ij}^{U(old)} + w_{ij}^{L(old)}}{2})
\end{align*}
\]

(5)

Where \( \eta \) is a learning rate. From this step, we can clearly see that the learning process is only to adjust the weights of the \( p \)-th and the \( m \)-th clusters.

**Step 6:** Repeat Step 2 to Step 5, if all patterns have been classified, then a learning epoch is finished.

**Step 7:** Stop, if the clustering process has converged, or the total error has arrived at a preset value, otherwise, return to Step 3.

3. The proposed forecasting method

In this paper, GDP growth and economic growth rates are the input factors of the forecasting model, and the YPL and YED are the output values. Due to the nonlinear relation between input factors and output values, the forecasting of the YPL and YED are not easy work. The main ideas of the proposed forecasting method divide into two parts. First, we use a novel clustering method based on the ENN to recognize the type of every year. When the GDP growth and economic growth rates are given, the changed ranges of YPL and YED at the forecast times can be forecasted according to the forecasting models. Second, using the multi-regression analysis method to build the forecasting model of every load type, when the GDP growth and economic growth rates are given, the forecasting values can be calculated according to the most similar load model. The proposed forecasting method is described as follows:

Step 1: According to the yearly peak load and electricity demand growth rates delimit some load types.
Step 2: Building the forecasting model of every load types as follows:

a. Use the ENN to learning the clustering models of every load type, the detail learning method can refer to the section 2;

b. The forecasting model of every load type can be calculated by the multi-regression analysis method as in section III, the typical forecasting model of i-th load type in our problem can be written as:

\[
y_i = b_{i0} + b_{i1}x_1 + b_{i2}x_2
\]

(7)

Where \( x_1 \) and \( x_2 \) are the GDP growth and economic growth rates of the forecasting data, respectively.
Step 3: Input the forecasting data, such as GDP growth and economic growth rates, determining the load type of the forecasting data by the ENN based clustering method.

Step 4: Use the forecasting model of this type as Eq. (7) to calculate the YPL and YED of the forecasting data.

4. Case studies and discussions

In Table I, the YED data from 1982 to 2001 is between 2.2% and 12.03% and can be divided into five types. To verify the proposed forecasting methods, Taiwan power (Taipower) system YPL, YED, GDP and economic growth rate data form 1982 to 2003 [1], twenty-two years data are utilized for experimentation. Figs. 1 and 2 show the relation between the input factors and output values. It is clear that the relations between the input factors and output values are highly non-linear curves. So if the forecasting models are directly to use the MRAM, the forecasting error will be large, which is the main reason in the proposed method to delimit some load types (or some sections) in the related curves. When the load types are delimited, every load type (or section) can be seen as approximately linear, thus the sectioned forecasting models will provide higher accuracy.

This paper uses the historical data from 1982 to 2001 to build the forecasting models, and the forecasting models to forecast the YPL and the YED from 2002 to 2003. Comparisons of forecasting results using the grey GM (1,1) model are also conducted [8]. Table II shows the compared results in years 2002 and 2003 with the different forecasting methods. The compared results of modeling accuracy are shown in Fig. 3, there are promising results were obtained by using the proposed forecasting method not only in the YED model or in the YPL model (1982 to 2001) but also in the forecasting values (2002 to 2003). The average error of all methods is shown in Table III. The average errors of the proposed method in both the YED and YPL are only 0.365% and 0.572%, respectively. On the other hand, the average errors of the grey GM(1,1) model are 3.18% and 6.569%. Therefore, the compared results also show that the proposed forecasting method has the higher accuracy than the grey GM(1,1) method.

### Table I The YED, YPL, GDP and economic growth data in Taiwan.

<table>
<thead>
<tr>
<th>Year</th>
<th>YED (KLOE)</th>
<th>YPL (MW)</th>
<th>GDP (NT$)</th>
<th>Economic growth rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1982</td>
<td>10,130,800</td>
<td>6,918</td>
<td>1,899,971</td>
<td>3.55</td>
</tr>
<tr>
<td>1983</td>
<td>11,308,300</td>
<td>7,808</td>
<td>2,100,005</td>
<td>8.45</td>
</tr>
<tr>
<td>1984</td>
<td>12,365,800</td>
<td>8,517</td>
<td>2,343,078</td>
<td>10.6</td>
</tr>
<tr>
<td>1985</td>
<td>12,988,600</td>
<td>8,716</td>
<td>2,473,786</td>
<td>4.95</td>
</tr>
<tr>
<td>1986</td>
<td>14,551,900</td>
<td>9,900</td>
<td>2,855,180</td>
<td>11.64</td>
</tr>
<tr>
<td>1987</td>
<td>16,100,100</td>
<td>11,113</td>
<td>3,237,051</td>
<td>12.74</td>
</tr>
<tr>
<td>1988</td>
<td>17,838,000</td>
<td>12,331</td>
<td>3,523,193</td>
<td>7.84</td>
</tr>
<tr>
<td>1989</td>
<td>19,449,500</td>
<td>13,422</td>
<td>3,938,826</td>
<td>8.23</td>
</tr>
<tr>
<td>1990</td>
<td>20,857,500</td>
<td>14,511</td>
<td>4,307,043</td>
<td>5.39</td>
</tr>
<tr>
<td>1991</td>
<td>23,107,900</td>
<td>15,321</td>
<td>4,810,705</td>
<td>7.55</td>
</tr>
<tr>
<td>1993</td>
<td>26,075,200</td>
<td>17,666</td>
<td>5,918,376</td>
<td>7.01</td>
</tr>
<tr>
<td>1994</td>
<td>27,888,000</td>
<td>18,610</td>
<td>6,463,600</td>
<td>7.11</td>
</tr>
<tr>
<td>1995</td>
<td>29,629,700</td>
<td>20,000</td>
<td>7,017,933</td>
<td>6.42</td>
</tr>
<tr>
<td>1996</td>
<td>31,449,800</td>
<td>22,000</td>
<td>7,678,126</td>
<td>6.15</td>
</tr>
<tr>
<td>1997</td>
<td>34,137,700</td>
<td>22,900</td>
<td>8,328,780</td>
<td>6.68</td>
</tr>
<tr>
<td>1998</td>
<td>36,590,800</td>
<td>23,830</td>
<td>8,938,967</td>
<td>4.57</td>
</tr>
<tr>
<td>1999</td>
<td>39,867,800</td>
<td>24,206</td>
<td>9,289,929</td>
<td>5.42</td>
</tr>
<tr>
<td>2000</td>
<td>44,162,100</td>
<td>25,854</td>
<td>9,663,388</td>
<td>5.86</td>
</tr>
<tr>
<td>2001</td>
<td>45,135,400</td>
<td>26,290</td>
<td>9,506,624</td>
<td>-2.18</td>
</tr>
<tr>
<td>2002</td>
<td>47,467,200</td>
<td>27,117</td>
<td>9,748,811</td>
<td>3.59</td>
</tr>
<tr>
<td>2003</td>
<td>49,623,300</td>
<td>28,129</td>
<td>9,847,555</td>
<td>3.24</td>
</tr>
</tbody>
</table>

Power : 1 KWH = 956 KLOE
KLOE : kiloliters Oil Equivalent

5. Conclusions

Economic development is based the electricity. The growth of electrical demand reflects the economic development and the industrial development at that time. This paper presents a novel forecasting method combining both the extension neural network and the MRAM. The proposed method not only can be used to forecast the values of YED
and YPL, it also can be used with multi-input factors in highly non-linear forecasting problems. The main advantage of the proposed method is that it can give the forecasting range and forecasting value at the same time. Moreover, the computing time of the proposed method is also short. Using practical numerical comparisons with the grey GM (1,1) model show that the proposed forecasting method has better accuracy and provides more information to planners on both YED and YPL forecasting.

<table>
<thead>
<tr>
<th>Items</th>
<th>YED (KLOE)</th>
<th>YPL (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2002</td>
<td>2003</td>
</tr>
<tr>
<td>Actual Data</td>
<td>47,467,000</td>
<td>49,623,000</td>
</tr>
<tr>
<td>Grey GM(1,1) method</td>
<td>Forecasting values</td>
<td>49,291,500</td>
</tr>
<tr>
<td>Forecasting error (%)</td>
<td>3.84</td>
<td>6.57</td>
</tr>
<tr>
<td>Proposed method</td>
<td>Forecasting values</td>
<td>46,862,000</td>
</tr>
<tr>
<td>Forecasting error (%)</td>
<td>1.28</td>
<td>0.99</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Modeling methods</th>
<th>YED average error (%)</th>
<th>YPL average error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed method</td>
<td>0.36479%</td>
<td>0.5717%</td>
</tr>
<tr>
<td>GM(1,1) method</td>
<td>3.1788%</td>
<td>6.5693%</td>
</tr>
</tbody>
</table>

Fig. 1 The relation of YED, YPL and GDP growth rates.
Fig. 2 The relation of YED, YPL and economic growth rates.

Fig. 3 The comparison between the actual Load data and the modeling data with the different methods.
Acknowledgments

The author gratefully acknowledges the part support of the National Science Council, Taiwan, ROC, under the grant no. NSC-95-2213-E-167-025-MY2.

References


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