Transactions on Power Systems, Vol. 7, No. 1, February 1992

SHORT-TERM LOAD FORECASTING USING AN ARTIFICIAL NEURAL NETWORK

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Abstract - Artificial Neural Network (ANN) Method is applied to forecast the short-term load for a large power system. The load has two distinct patterns: weekday and weekend-day patterns. The weekend-day pattern include Saturday, Sunday, and Monday loads. A nonlinear load model is proposed and several structures of ANN for short-term load forecasting are tested. Inputs to the ANN are past loads and the output of the ANN is the load forecast for a given day. The network with one or two hidden layers are tested with various combination of neurons, and results are compared in terms of forecasting error. The neural network, when grouped into different load patterns, gives good load forecast.

Keywords - Neural network, load forecasting, backpropagation algorithm

1. INTRODUCTION

In order to supply high quality electric energy to the customer in a secure and economic manner, an electric company faces many economical and technical problems in operation, planning, and control of an electric energy system. For the purpose of optimal planning and operation of this large scale system, modern system theory and optimization techniques are being applied with the expectation of considerable cost savings. In achieving this goal, the knowledge of future power system load is the first prerequisite; therefore, long- and short-term load predictions are very important subjects.

The load prediction period may be month or year for the long- and the medium-term forecasts[1], and day or hour for the short-term forecast[2-7]. The long- and the medium-term forecasts are used to determine the capacity of generation, transmission, or distribution system additions, and the type of facilities required in transmission expansion planning, annual hydrothermal maintenance scheduling, etc. The short-term forecast is needed for control and scheduling of power system, and also as inputs to load flow study or contingency analysis.

There are several classes of load forecasting models reported in literature[8]. Some load models which use no weather information have been represented by time sequences[2-4]. The other load models have included the effects of weather variables on the power system load[5-7]. The former is based on the extrapolation and the load behavior is represented by Fourier series or trend curves in terms of time functions[2]. More recently, state variable models[3] and autoregressive-moving average(ARMA) models[4] have also been developed to describe the load behavior. For the models including weather variables, the total load is decomposed into the weather sensitive load and the non-weather sensitive load[5-7]. The weather sensitive load is mostly predicted using the correlation techniques and the non-weather sensitive load is modeled by the method mentioned above. Each load component is predicted separately and the sum gives the forecast of the total load.

There is another approach that doesn't assume specific load model but try to find the rule between the historical load data and dry-bulb temperature from the expert system point of view [9]. The objective of this approach is to use the knowledge, experience and analogical thinking of experienced system operators. Recently authors developed a new method of adaptively identifying the load model which reflects the stochastic behavior without the aid of weather variables [10]. They decomposed the load model into three components: the nominal load, the residual load, and the type load. The parameters of the model are adapted to the load variations.

Forecasting has been mentioned as one of the most promising application areas of artificial neural network (ANN). Several authors have attempted to apply the backpropagation learning algorithm [11] to train ANNs for forecasting time series. Application of this idea to the real world problem can be found in Werbos's work [12], where he applied the backpropagation algorithm to the recurrent gas market model. There was also a negative opinion [13] that the forecasting ability of the backpropagation algorithm was inferior to simple linear regression. Recently, however, the National Science Foundation organized a workshop to address the importance of ANNs in power system engineering, and authors demonstrated that ANN can be successfully used in short-term load forecasting with accepted accuracy [14].

In this paper the backpropagation algorithm is proposed as a methodology for electric load forecasting. A nonlinear load model is suggested and the parameters of the nonlinear load model are estimated using the backpropagation algorithm. Test result shows a satisfactory use of the ANN, and the percentage forecasting error was about 2 %.

2. CLASSIFICATION AND CHARACTERISTICS OF LOADS

Fig. 1 illustrates the hourly load curves for February 8-21, 1987. The figure shows daily and weekly load variations; the load behavior for weekdays (Tuesday through Friday) has a same pattern but small random variations from varying industrial activities, weather conditions, etc. The weekday load pattern is different from Saturday, Sunday, and Monday load patterns. Comparing weekday loads with Saturday loads, the

91 WM 199-0 PWRS A paper recommended and approved by the IEEE Power System Engineering Committee of the IEEE Power Engineering Society for presentation at the IEEE/PES 1991 Winter Meeting, New York, New York, February 3-7, 1991. Manuscript submitted June 25, 1990; made available for printing January 3, 1991.

level of Saturday loads is relatively low during p.m.. The level of Monday loads during a.m. influenced by Sunday is very low. Also the 1st and the 3rd Sunday loads are lower than the 2nd and the 4th Sunday loads due to reduction in industrial or commercial activities observed in Korea [10]. These phenomena equally affects Monday loads during a.m.. Therefore daily load curves are classified as weekday and weekend-day patterns. The weekend-day patterns are grouped into five different type loads $d = (1, 2, \cdots, 5)$: Saturdays ($d = 1$), the 1st and the 3rd Sundays ($d = 2$), the 2nd, the 4th and the 5th Sundays ($d = 3$), the 1st and the 3rd Mondays ($d = 4$), the 2nd, the 4th and the 5th Mondays ($d = 5$), except special holidays.

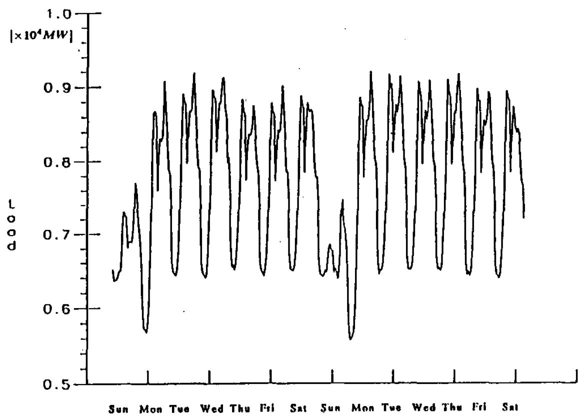


Fig. 1 Hourly load curve over two weeks

3. ARTIFICIAL NEURAL NETWORK

An artificial neural network (ANN) as a computing system is made up of a number of simple, and highly interconnected processing elements, which processes information by its dynamic state response to external inputs. In recent times the study of the ANN models is gaining rapid and increasing importance because of their potential to offer solutions to some of the problems which have hitherto been intractable by standard serial computers in the areas of computer science and artificial intelligence. Neural networks are better suited for achieving human-like performance in the fields such as speech processing, image recognition, machine vision, robotic control, etc.

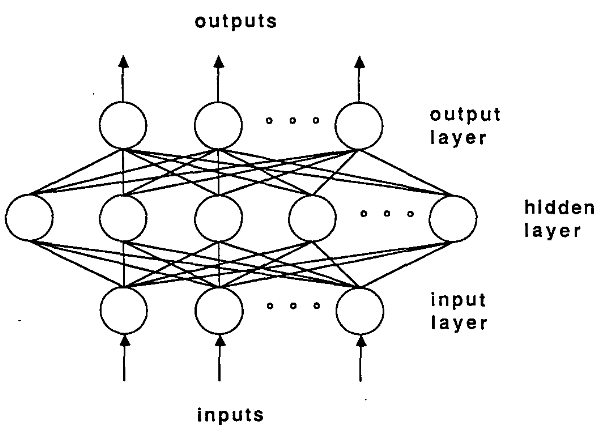


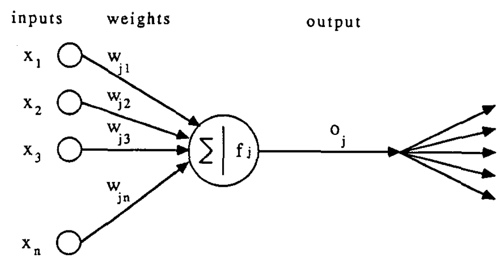
Fig. 2 Schematic of feedforward neural network

Fig. 2 shows a schematic of a generic feedforward network which is the most commonly used ANN model. Processing elements in an ANN are also known as *neurons*. These neurons are interconnected by means of information channels called interconnections. Each neuron can have multiple inputs, while there can be only one output (Fig. 3 a). Inputs to a neuron could be from external stimuli or could be from output of the other neurons. Copies of the single output that comes from a neuron could be input to many other neurons in the network. It is also possible that one of the copies of the neuron's output could be input to itself as a feedback. There is a connection strength, *synapses*, or weight associated with each connection. When the weighted sum of the inputs to the neuron exceeds a certain threshold, the neuron is fired and an output signal is produced. The network can recognize input patterns once the weights are adjusted or tuned via some kind of learning process.

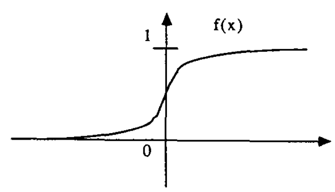
The *backpropagation* learning algorithm is the most frequently used method in training the networks, and proposed as an electrical load forecasting methodology in this paper. For the completeness of the paper, the backpropagation algorithm will be introduced briefly.

The backpropagation learning algorithm is a generalization of the Widrow-Hoff error correction rule [15]. The original Widrow-Hoff technique formed an error signal, which is the difference between what the output is and what it was suppose to be, i.e., the reference or target output. Synaptic strengths, or weights, were changed in proportion to the error times the input signal, which diminishes the error in the direction of the gradient.

In a multilayer network (Fig. 2) containing *hidden* units, that is, units that are neither input nor output units, the problem is much more difficult. The error signal can be formed as before, but many synapses can give rise to the error, not just the ones at the output units. Since we usually do not know what the target outputs of the hidden units are, we cannot directly compute the error signal for hidden units.



(a) Mathematical model of neuron



(b) Sigmoid function

Fig. 3 Schematic of an artificial neuron

The "generalized delta rule" is suggested by Rumelhart, et al. and gives a recipe for adjusting the weights on internal units based on the error at the output [11]. To be more specific, let

$$E_p = \frac{1}{2}\sum_j (t_{pj} - o_{pj})^2, \quad (1)$$

be the measure of error on pattern p and let $E = \sum_p E_p$ be the overall measure of the error, where t_{pj} is the target output for j-th component of the output pattern for pattern p and o_{pj} is the j-th component of the actual output pattern produced by the network representation with input pattern p.

The network is specified as

$$o_{pj} = f_j(net_{pj}), \quad (2)$$

$$net_{pj} = \sum_k w_{jk} o_{pk}, \quad (3)$$

where f_j is a differentiable and nondecreasing function and w_{jk} is a weight to be adjusted. The function f_j is normally a sigmoid type function as shown in Fig. 3 b.

To obtain a rule for adjusting weights, the gradient of E_p with respect to w_{ji} is used and it is represented as follows :

$$-\frac{\partial E_p}{\partial w_{ji}} = \delta_{pj} o_{pi}, \quad (4)$$

where δ_{pj} is defined in two ways. If a unit is an output unit, it is given by

$$\delta_{pj} = (t_{pj} - o_{pj}) f_j'(net_{pj}), \quad (5)$$

and for a unit in an arbitrary hidden layer

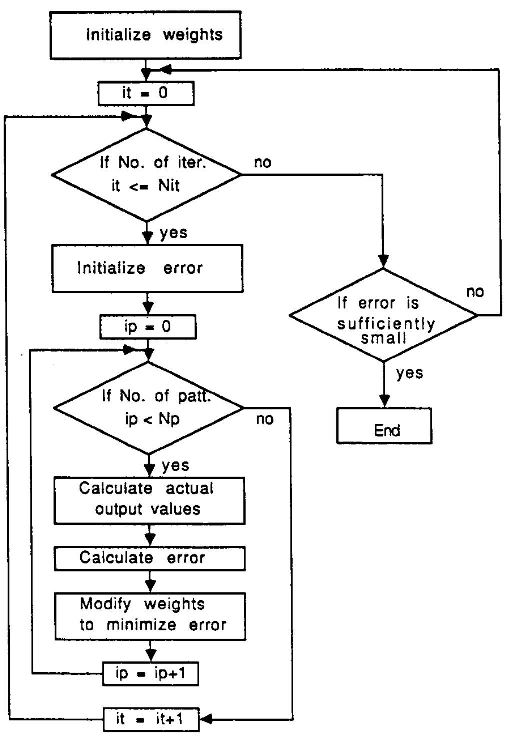


Fig. 4 Flowchart for the backpropagatin algorithm

$$\delta_{pj} = f_j'(net_{pj}) \sum_k \delta_{pk} w_{kj}, \quad (6)$$

where f_j' is the derivative of f_j.

The rule of adjusting weights can be derived using eq. (4), and given as

$$\Delta w_{ji}(n+1) = \eta \delta_{pj} o_{pi} + \alpha \Delta w_{ji}(n), \quad (7)$$

where η is the learning rate parameter and α is the momentum constant to determine the effect of past weight changes. The flowchart for the backpropagation learning algorithm following eqs. (1)-(7) is shown in Fig. 4.

4. LOAD FORECASTING USING BACKPROPAGATION ALGORITHM

In this section two different methods of application of ANN are presented in the short-term load forecasting. Method 1 is a *static approach* which forecast the 24-hour load simultaneously, while Method 2 is a *dynamic approach* in the sense that the 24-hour load is forecasted sequentially using the previous-time forecasts.

• Method 1

The load data were analyzed and the load patterns were classified. The current load is affected by the past loads and the pattern in which the current load is included. For example, Monday loads are affected by Sunday and Saturday loads and their patterns are similar. Therefore the following nonlinear load model is proposed for one-day ahead forecasting:

$$y(i) = F(W_i, Y(i-1)), \quad (8)$$

where

$y(i) = \{y(i,t) : t = 1, 2, \cdots, 24\}$: the actual load vector at day i

$y(i,t)$: the actual load at day i, time t

$Y(i-1) = [y(i-1), y(i-2), \cdots, y(i-k)]^T$

k : index for data length

W_i : the weight vector

$F(\cdot,\cdot)$: nonlinear vector function representing ANN.

In contrast to the conventional approaches, the nonlinear function is used with the weight vector to represent the load model. The weight vector W_i can be thought of as the storage that contains a certain load pattern, and $F(\cdot,\cdot)$ is the general nonlinear function that can comprise all the load patterns.

The load patterns were classified into weekday pattern and weekend-day patterns. In order to forecast the load $y(i)$ the weight vector W_i should be estimated using previous load data for each pattern.

Weekdays

To estimate the weekday load pattern for day i, three latest weekdays are used to adjust the weight as follows:

$$y(i-1) = F(\hat{W}_i, Y(i-2)), \quad (9)$$

where the output data $y(i-1)$ is the latest weekday load, the input data $Y(i-2) = [y(i-2), y(i-3)]^T$ is the next two latest weekday loads and $\hat{W}_i$ is the estimated weight vector using these input and output data.

Weekend-days

To estimate the weekend-day load pattern, the weekend-day load patterns are grouped into five different type loads, and the following scheme is proposed:

$$y(\underline{i}_d) = F(\hat{W}_i, Y(\underline{i}_d - 1)), d = 1, 2, \cdots, 5, \tag{10}$$

where $\underline{i}_d$ represents the previous type d day. For example, $\underline{i}_1$ represents the previous Saturday when day i is a Saturday; $\underline{i}_2$ for the previous 1st or 3rd Sunday; $\underline{i}_3$ for the previous 2nd, 4th or 5th Sunday, etc.

The weight vector is adjusted using eqs. (9) or (10) according to the pattern in which the load to be forecasted is included. The error backpropagation algorithm is used to decrease the error, for example, in the case of weekdays

$$E = (y(i-1) - F(\hat{W}_i, Y(i-2))^T (y(i-1) - F(\hat{W}_i, Y(i-2)), \tag{11}$$

is minimized following the rule, eq. (7), until the error decreases to a predetermined tolerance.

Once the weight vector for day i is estimated, the load is forecasted using the following equation:

$$\hat{y}(i) = F(\hat{W}_i, Y(i-1)). \tag{12}$$

where $\hat{y}(i)$ indicates the load forecast for day i.

The above scheme was simulated and errors in forecasting were analyzed. The result was fairly good except day time hours. Therefore the above scheme is used for three parts, namely 1-9, 10-19 and 20-24 hour forecastings, and the resulting three model constitute the daily load forecasting as follows:

$$\hat{y}(i) = \begin{cases} F(\hat{W}_i^1, Y(i-1)), & t \in T_1 = \{1, \cdots, 9\} \\ F(\hat{W}_i^2, Y(i-1)), & t \in T_2 = \{10, \cdots, 19\} \\ F(\hat{W}_i^3, Y(i-1)), & t \in T_3 = \{20, \cdots, 24\}, \end{cases} \tag{13}$$

where $\hat{W}_i^j$ corresponds to the estimated weight vector for time band T_j. Here the input data $Y(i-1)$ is common and contains the previous 48 hour data, but the output $\hat{y}(i)$ depends on the time band and contains 9, 10, or 5 hour data.

- Method 2

Another important characteristic of load is shown in Fig. 5 which gives the autocorrelation function of hourly load over four weeks. The function shows peaks at the multiples of 24 hour lags, which indicates that the loads at the same hours have very strong correlation with each other independent of the day of the week including weekend-days. Thus the following load model is proposed:

$$\begin{aligned} y(i,t) = F(W(i,t), & y(i,t-1), y(i,t-2), \cdots, y(i,t-m), \\ & y(i-1,t), y(i-1,t-1), \cdots, y(i-1,t-m), \\ & \vdots \\ & y(i-n,t), y(i-n,t-1), \cdots, y(i-n,t-m)), \end{aligned} \tag{14}$$

where n and m indicate the data length.

The load patterns were classified into weekday pattern and weekend-day pattern. The weight vector $W(i,t)$ is estimated at each time using previous load data for each pattern in a similar way as eqs. (9) and (10).

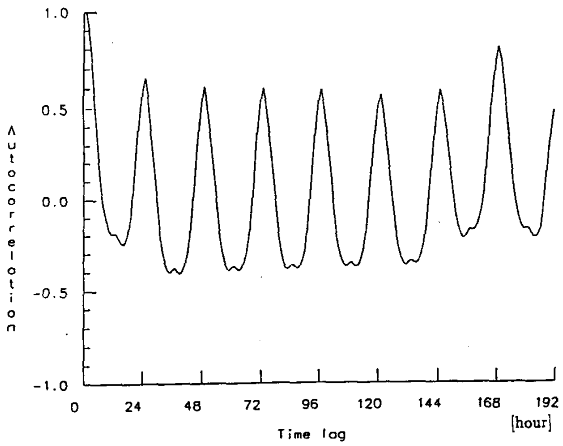


Fig. 5 Autocorrelation of hourly load

After the weight vector at day i, time t is estimated, the load is forecasted with the load data of previous days as well as the forecasted load data for the same day at previous time steps as follows:

$$\begin{aligned} \hat{y}(i,t) = F(\hat{W}(i,t), & \hat{y}(i,t-1), \hat{y}(i,t-2), \cdots, \hat{y}(i,t-m), \\ & y(i-1,t), y(i-1,t-1), \cdots, y(i-1,t-m), \\ & \vdots \\ & y(i-n,t), y(i-n,t-1), \cdots, y(i-n,t-m)), \end{aligned} \tag{15}$$

where $\hat{y}(i,t)$ indicates the load forecast at day i, time t.

Note that Method 2 has only one output while Method 1 has 24 outputs. This means there are less number of weights in Method 2. Since eq. (15) is for each time, total number of weights for 24-hour is about the same. However, Method 2 requires much less number of inputs for comparable accuracy, and, consequently, the total number of weights is much less. This will be demonstrated numerically in the following section.

5. DISCUSSION

Case studies for the proposed method were carried out for a one-day ahead forecasting of hourly electric loads using a historical utility data of Korea Electric Power Company [10]. The results were obtained for four representative months in four seasons. These months are February, May, July, and October for Winter, Spring, Summer and Fall, respectively, and the results were analyzed by the following indices:

(i) Standard deviation

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [y(i,t) - \hat{y}(i,t)]^2}$$

(ii) Percent relative error

$$\varepsilon = \frac{1}{N} \sum_{i=1}^{N} |y(i,t) - \hat{y}(i,t)| \cdot 100 / y(i,t).$$

Several structures of ANN with the backpropagation learning algorithm were tested. The learning rate η and the momentum constant α in eq. (7) were fixed to 0.75 and 0.1, respectively. In the case of Method 1, the tolerance of adjusting the weight vector was 0.005. As described in section 4, the ANN was trained using the data for three latest available days for each load model. For example, in the case of the weekday model, the latest 24 hour data is used for output and the next two latest day loads of 48 hours for input data. After the training is done, then the model advances by one day to predict the future 24 hour loads using the latest 48 hour load data. The number of neurons in the input layer was 48 always for 48 hour data and the number of neurons for output layer were 9, 10, and 5 for time band T_1, T_2, and T_3, respectively. Since it is known that the three layer neural network with $2I+1$ neurons in the hidden layer is sufficient to represent a nonlinear function [16], only one hidden layer with 97 neurons was used initially. In this case the weight vector oscillated and the predetermined tolerance was not achieved. Thus, two hidden layers were used with various numbers of neurons in the first hidden layer and 24 neurons in the second hidden layer. In all cases the weight vector converged within a predetermined tolerance. The results were presented in Table 1.

Table 1 Comparison of forecasting results for various neurons

season	Winter				Summer			
no. of neurons	48	70	90	120	48	70	90	120
std. dev. [MW]	187	176	176	186	270	250	250	269
per. error [%]	1.84	1.67	1.67	1.84	2.37	2.18	2.18	2.36

The weight vector that minimizes the error is not unique and it gives different errors in forecasting although they were small. The better or similar results were obtained as the number of neurons in the first hidden layer increases to 90 neurons. But when the 120 neurons were used, the result was worse than those cases with 70 and 90 neurons.

Therefore the test was conducted with 70 neurons in the first hidden layer for all four seasons. The results were analyzed in detail on an hourly base and presented in Table 2. The results in Table 2 shows the successful application of the neural network for the short-term load forecasting. The percent relative error and the standard deviation for each season are in the bottom line of Table 2. The minimum values of the percent relative error and the standard deviation were found in Winter, which are 176.25 [MW] and 1.674%, respectively, and the maximum values were found in Summer, which are 249.61 [MW] and 2.184%, respectively.

In the case of Method 2, the tolerance of adjusting the weight vector was reduced to 0.0005 and the data lengths n and m were fixed to 2. Thus inputs are load for time t, $t-1$, and $t-2$ of two previous days and forecasted load for time $t-1$ and $t-2$ of the same day, totalling 8 inputs. The neural network with one hidden layer was simulated and 8, 17 and 1 neurons were used in the input, hidden, and output layers, respectively. The forecasting results were almost same as those of Method 1, but it results in the reduction of network size considerably. The minimum values of the percent relative error and the standard deviation were found in Winter, which are 173.06 [MW] and 1.676%, respectively, and the maximum values were found in Summer, which are 248.62 [MW] and 2.200%, respectively. Comparison between the forecasted load and the actual load data for two weeks as well as for one month in Winter are shown in Figs. 6 and 7, respectively.

Both Methods 1 and 2 were also carried out for a one-day-ahead load forecasting during six months from February to July. Test results are shown in Table 3 and compared with the results of authors' analytical method [10] which adaptively identifies the load model. The forecasting results of the Method 2 during six months were better than that of Method 1 mainly in day-time. Since the peak load occurs in day-time, the Method 2 gives more useful information for the short-term scheduling of power system. The average percent relative errors are 1.885% and 1.834% for Methods 1 and 2, respectively. These are compared with the error of 1.40% for the adaptive analytical method [10]. Since the adaptive analytical method gave a very accurate forecasting results compared to other existing conventional approaches, the ANN approach did not yield better results. However, the

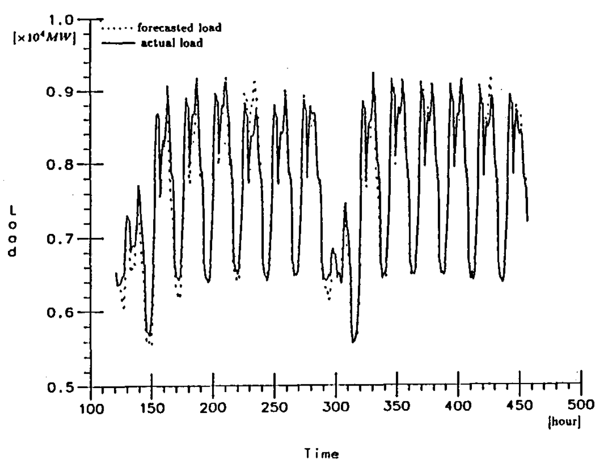


Fig. 6 Comparison of actual load and forecasted load for two weeks in Winter

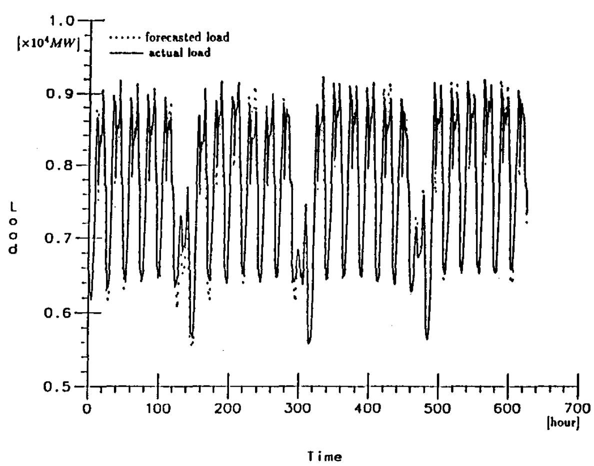


Fig. 7 Comparison of actual load and forecasted load for one month in Winter

relative error of less than 2% is still considered to be good and shows a promise for future applications.

The backpropagation algorithm was very robust in estimating the weights in nonlinear load model. The computation time of Methods 1 and 2 for 24-hour ahead load forecasting were 14.64 and 6.64 seconds, respectively, on the VAX 8550 computer.

Note that the weather variables were not used in the weight adjustment and forecasting. Addition of weather variables, past and forecast, will undoubtedly improve the forecasting accuracy. Nevertheless, the above results show comparable accuracy to conventional analytical approaches. Further improvement can also be achieved if additional parameters are introduced in defining the sigmoid function, e.g., slope and threshold of the function.

6. CONCLUSION

Artificial neural network method is applied to the short-term load forecasting of one-day ahead hourly electric loads in two different ways. A nonlinear load model is proposed and the weights are estimated using a backpropagation learning algorithm. The backpropagation algorithm is robust in estimating the weights in nonlinear equation. In all cases the backpropagation algorithm can find the weights within a predetermined tolerance.

The load patterns are classified into several patterns and a one-day ahead load forecasting is separated into three parts to increase the forecasting accuracy for day time hours in Method 1 and 24 parts in Method 2, which results in the reduction of network size with the same accuracy. The dynamic approach (Method 2) performs better than the static approach (Method 1) in the sense that it uses much less number of neurons and weights, trains faster, and gives better results, especially for the peaks. The proposed methods are tested using a historical utility load data. The forecasting error is about 2 % for the percent relative error and thus shows a promise for the use of artificial neural network method in load forecasting.

Table 3 Comparison of forecasting results

	Method 1		Method 2		Refer. [10]	
hour	std. dev.	per. err.	std. dev.	per. err.	std. dev.	per. err.
1	185.06	1.792	187.80	1.813	109.94	1.18
2	162.50	1.622	164.86	1.644	95.13	1.08
3	153.94	1.556	155.69	1.578	97.37	1.10
4	157.54	1.599	160.15	1.619	86.44	1.01
5	150.71	1.550	155.09	1.591	85.78	0.99
6	143.85	1.457	159.23	1.629	93.64	1.04
7	167.51	1.543	184.01	1.681	106.42	1.12
8	159.38	1.566	172.12	1.687	109.95	1.06
9	184.21	1.671	186.91	1.673	204.56	1.92
10	239.28	2.084	216.43	1.774	185.51	1.61
11	243.99	2.102	215.58	1.765	169.92	2.02
12	253.47	2.193	223.44	1.870	186.63	1.53
13	233.85	2.138	222.17	2.056	175.77	1.66
14	250.66	2.209	233.55	2.039	185.34	1.55
15	266.4	2.254	240.74	2.061	191.44	1.61
16	257.42	2.233	236.07	2.073	185.24	1.63
17	260.16	2.328	238.97	2.174	193.05	1.67
18	271.75	2.511	257.85	2.374	212.09	1.82
19	258.34	2.305	234.74	2.091	196.33	1.78
20	202.68	1.749	205.93	1.792	162.28	1.51
21	177.64	1.538	181.03	1.575	127.29	1.12
22	191.36	1.601	197.45	1.684	156.53	1.37
23	213.51	1.785	214.83	1.779	149.37	1.31
24	206.62	1.859	217.78	1.989	140.55	1.39
total	212.29	1.885	204.88	1.834	156.76	1.40

Table 2 Statistics of forecasting results

	Winter		Spring		Summer		Fall	
hour	std. dev.	per. err.	std. dev.	per. err.	std. dev.	per. err.	std. dev.	per. err.
1	110.29	1.263	247.18	2.379	201.00	2.071	192.21	1.978
2	79.98	1.023	209.63	2.246	178.73	1.937	177.83	1.855
3	91.59	1.156	199.53	2.129	145.43	1.635	185.76	1.991
4	105.02	1.278	189.57	1.999	168.83	1.790	178.19	1.887
5	132.77	1.621	174.09	1.835	134.70	1.495	172.47	1.869
6	124.20	1.476	156.34	1.519	158.89	1.621	171.06	1.905
7	174.68	1.757	169.37	1.613	172.39	1.620	199.42	1.998
8	134.73	1.266	204.47	2.196	189.52	1.821	199.34	2.010
9	169.81	1.611	199.64	1.734	246.61	2.231	250.27	2.346
10	212.11	1.891	255.92	2.257	295.67	2.556	265.14	2.309
11	192.78	1.792	254.73	2.267	290.25	2.346	267.83	2.325
12	206.53	2.030	274.53	2.426	290.41	2.403	369.38	2.573
13	189.57	1.862	248.98	2.333	296.32	2.719	236.36	2.266
14	214.26	2.165	235.91	2.193	299.96	2.643	257.20	2.260
15	200.83	1.929	256.69	2.249	320.82	2.576	250.96	2.246
16	203.22	2.003	259.67	2.354	295.65	2.485	244.28	2.286
17	247.37	2.537	249.72	2.219	285.02	2.342	269.20	2.550
18	306.17	3.155	210.57	1.862	263.94	2.387	312.95	2.709
19	272.34	2.488	223.18	1.950	229.49	1.958	285.34	2.385
20	128.21	1.044	209.03	1.900	263.28	2.294	211.20	1.693
21	161.83	1.339	160.48	1.594	261.04	2.312	203.66	1.688
22	96.98	0.928	244.06	2.156	256.71	2.304	221.01	1.716
23	125.57	1.308	268.58	2.325	278.63	2.411	203.89	1.708
24	108.87	1.260	251.47	2.370	307.92	2.467	203.67	1.997
total	176.25	1.674	225.78	2.088	249.61	2.184	235.31	2.106

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BIOGRAPHIES

Kwang Y. Lee was born in Pusan, Korea, on March 6, 1942. He received the B.S. degree in Electrical Engineering from Seoul National University, Seoul, Korea, in 1964, the M.S. degree in Electrical Engineering from North Dakota State University, Fargo, in 1968, and the Ph.d. degree in System Science from Michigan State University, East Lansing, in 1971.

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June H. Park was born in Masan, Korea, on September 17, 1955. He received the B.S., M.S., and Ph.D. degree in Electrical Engineering from Seoul National University, Seoul, Korea, in 1978, 1980, and 1987, respectively. He has been on the faculties of Chung-Nam National University, Pusan National University, where he is an Associate Professor of Electrical Engineering. His areas of interest are power system control, operation, and planning.

Dr. Park has been a member of the Korea Institute of Electrical Engineers.

Discussion

M. S. Kurzyn, (Victoria College Clayton, Vic., Australia): The authors should be commended for coming up with an unorthodox solution to the problem of short-term load forecasting in power systems. There are three areas of the presented research that seem to require further clarification:

1. The authors have developed a specific neural network which uses the backpropagation learning algorithm for error correction. However, it should be noted that several other neural networks are available, e.g., the Kohonen network, the avalanche network, the ART network. What were the reasons, if any, behind choosing the authors' ANN?
2. The recent study [1] indicates that higher forecasting error can be expected during start-up days, i.e., Mondays, and during variant days, i.e., holiday seasons. Could the authors show their forecasting results for such days?
3. What were the training times and the run times for trained ANNs in the case studies presented?

The authors' response addressing the above points would be highly appreciated.

Reference

[1] D. C. Park *et al*, "Electrical Load Forecasting using an Artificial Neural Network," IEEE PES Summer Meeting, Minneapolis, MN, July 1990, paper no 90 SM 377-2 PWRS.

Doug C. Park and **Osama A. Mohammed** (Florida International University, Miami, Florida): This paper proposes an application of an Artificial Neural Network (ANN) to short-term load forecasting. However, this technique was thoroughly studied in a previous paper [1] which is not included in the list of references. The paper by D. C. Park *et al* describes how to apply the ANN to forecast 1) the peak load of the day, 2) the total load of the day, and 3) hourly load. For the case of hourly load forecasting, the lead time varies 1-24 hours in the paper. The paper [1] also utilizes weather information in addition to the past load profiles.

These discussers think that this paper is a subset of the previous paper [1], in the sense that it discusses only hourly load forecasting with lead time of 24 hour and the network utilizes only past load information. The differences between the two papers include: 1) weekend forecasting, 2) two more hourly loads of previous days, and 3) three different models for different hours of a day.

Regardless of the above, these discussers have the following questions and would like to have the author's clarification: First, the paper includes weekend load forecasting. The weekend load forecasting, however, is not much different from weekdays' forecasting in terms of technical effort. Furthermore, utility companies have little interest in weekend load forecasting since the load demand of weekend is much smaller than that of weekdays.

Second, the paper includes more input variables of previous load data. In our experience, more input neurons often do not give better performance with given number of training data. More input neurons make the performance of the neural network worse in many circumstances unless the extra input neurons are essential and enough training data are provided.

Finally, the authors use three different models for different hours of a day (one for hour 1-9, one for hour 10-19, and one for hour 20-24) instead of using an input neuron which describes the hour of a day. We, however, believe that this really makes the performance of the neural network bad since this assumes the training data have the same characteristic in the same block of hours. Each individual hour should have different system characteristic. Also by making three different models it creates the problem of *edge effect*. This affects the results shown in Tables 2 and 3 of the paper. The networks are experiencing higher error ratio at most of the hours in the border of the blocks (hours 1, 9, 10, 20, and 24) comparing to the errors at the rest of hours.

Reference

[1] D. C. Park, M. El-Sharkawi, R. Marks II, L. Atlas, and M. Damborg, "Electric Load Forecasting Using An Artificial Neural Network," IEEE/PES 1990 Summer Meeting, Minneapolis, MN, July 15-19, 1990, Paper #90 SM 377-2 PWRS.

Manuscript received February 20, 1991.

K. Y. Lee, Y. T. Cha, and **J. H. Park**: The authors thank the discussers for their genuine interests in the paper and their comments.

The authors appreciate the discussers for bringing up the fine paper by D. C. Park, *et al.* which was presented at the IEEE/PES 1990 Summer Meeting, July 15-19, 1990. Unfortunately, the authors were not aware of the referenced paper while they were working on their paper. As one may notice, this paper was in fact submitted to the IEEE/PES on June 25, 1990, which is before the date of the Summer Meeting.

Professors Park and Mohammed kindly pointed out differences between the two papers. Two papers are obviously different because their objectives are different. The use of the load forecasting model for the KEPCO includes the unit committment and economic dispatch. Therefore, the weekend load forecasting is as important as the weekday's. In fact, the weekend forecasting is more important to KEPCO because it is a much more difficult problem due to the changing work schedule observed in Korea during weekends. That is why five different types of loads are considered for weekends.

Many utilities in U.S. trade energy with neighboring ones, and thus the forecasting of peak load is very important. However, the KEPCO is the only utility in Korea, and thus the peak load forecasting is not considered to be as important as in the U.S.A.

Professors Park and Mohammed correctly pointed out that this paper uses more input variables of previous load data. Method 1 uses 48-hour data as input, but it gives in turn 24-hour load forecasting as output. This means that the input/out ratio is only 2. In an analytic forecasting model the use of 2 days worth data for the 1 day forecasting is considered to be very fair (see ref. [10] in the paper). The authors agree with the discussers' comments that more neurons make the performance of the network worse unless the extra input neurons are essential. If one wants the 24-hour load forecasting done *at once*, the cyclical load pattern contained in the 1 to 2 days maybe viewed as minimal. Nevertheless, the difficulty of handling a large number of neurons was experienced, and Table 1 in the paper summarizes this experience.

Method 2 was developed in the spirit of the discussers, and reduced the number of input variables to 8. It uses 3 load data points per day for 2 previous days and 2 load data forecasted for the previous 2 hours in the same day. This method is comparable to the case 3 of the paper by D. C. Park, *et al.*, where 6 input variables are used. However, an important distinction of this paper is that it does not use temperature data. In spite of this, it gives comparable accuracy as it is compared with an analytic method in Table 3 of the paper. Temperature data is obviously a very important factor affecting the load. However, its value is often limited to the confidence level on weather forecasting. Therefore, unless the weather forecasting is very accurate, much care should be made on the use of temperature data.

The discussers very well pointed out the *edge effect* of using three different models for Method 1. This is another reason why Method 2 was developed and preferred over Method 1. The use of the hour of a day as an additional input, suggested by the discussers, is also a very good idea.

Dr. Kurzyn addressed an important issue on the choice of a suitable network. The feedforward network is first selected because of its simplicity of the architecture and the training algorithm. Another important improvement that we later made is Method 3, where the feedforward network in Method 2 is replaced by the recurrent neural network [1]. It allows us to use much less number of neuron for comparable accuracy.

Dr. Kurzyn well pointed out that higher forecasting error can be expected during start-up days, such as Mondays. This is another reason why the weekend forecasting problem was handled more carefully than weekdays in this paper. The weekends, which include Mondays in the paper (type $d = 5$), are shown in Figures 6 and 7 in the paper.

As discussed in the paper in Section 5, the computation time, including the training time and the run times, for Methods 1 and 2 for 24-hour ahead load forecasting were 14.64 and 6.64 seconds, respectively.

Finally, the authors would like to point out that Professors Park and Mohammed mistakenly interpret that the paper discusses only hourly load forecasting with lead time of 24 hour. This interpretation is true for Method 1. However, in Method 2 the lead time varies from 1 to 24 hours since the forecasting is done on an hourly basis starting from the hour 1.

Again, the authors appreciate the comments of discussers and their interests.

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[1] K. Y. Lee, Y. T. Cha, and C. C. Ku, "A study on Neural Networks for Short-Term Load Forecasting," *Proceedings of the First International Forum on Applications of Neural Networks to Power Systems*, pp. 26-30, Seattle, Washington, July 23-26, 1991.

Manuscript received August 6, 1991.