

Implementation of Neural Network Approach for Short term Load forecasting

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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 includes 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 is tested with various combinations 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, Back Propagation, load forecasting, correlation etc.,

I. INTRODUCTION

The electricity supply industry requires to forecast electricity demand with lead times that range from the short term (a few minutes, hours, or days ahead) to the long term (up to 20 years ahead). Short-term forecasts, in particular, have become increasingly important since the rise of the competitive energy markets. Short term forecasting of electrical load is important for optimum operation planning of power generation facilities as it affects both system reliability and fuel consumption. Accurate forecasting of electricity and power demand determines the utility to match its generation capabilities to the expected requirements. Electric utility operators for the purpose of scheduling and dispatching generating units need short-term forecasts. A short-term forecast is important for "unit commitment, economic dispatch, hydrothermal co-ordination, load management, etc." Ackerman [12] says that a short-run forecast plays an important role in the day-to-day operations of a utility, and it is typically used for optimizing system operation and scheduling of hydro units and other peaking plants, such as gas turbines. The objective of the operators is to minimize variable costs without jeopardizing the electric system to power failures. The short-term (one to twenty-four hour) load forecast is of importance in the daily operations of the utility. With the emergence of Load Management, the short-term load forecast has a broader role in utility operations; it is also required for the co-ordination of Load Management programs with conventional system resources. Since the effectiveness of Load Management programs is sensitive to the system load, this additional function places higher accuracy requirements on the short term forecast, also required for short term maintenance scheduling. Accurate forecasting of power demand is to determine the assessment of the dynamic behavior of the system during disturbances so that the proper preventive action can be taken up. Load forecasting is however a difficult task. First, because the load series is complex and exhibits several levels of seasonality: the load at a given hour is dependent not only on the load at the previous hour, but also on the load at the same hour on the previous day, and on the load at the same hour on the day with the same denomination in the previous week. Secondly, there are many important exogenous variables that must be considered, especially weather-related variables. It is relatively easy to get forecast with about 10 % mean absolute error; however, the cost of error are so high that research could help to reducing it in a few percent points would be amply justified. Most forecasting models and methods have already been tried out on load forecasting, with varying degrees of success. They may be classified as *time series models*, in which the load is modeled as a function of its past observed values, and *causal models* in which the load is modeled as a function of some exogenous factors, especially weather and social variables. Some models of the first class suggested in recent papers are multiplicative autoregressive models, dynamic linear or nonlinear

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models, threshold autoregressive models, and methods based on Kalman filtering. Some of the second classes are Box and Jenkins transfer functions, ARMAX models, optimization techniques, nonparametric regression, structural models, and curve-fitting procedures. Despite this large number of alternatives, however, the most popular causal models are still the linear regression ones and the models that decompose the load, usually into basic and weather dependent components [11]. In Functional-Link Network (FLN) model of hybrid neural networks, a non-linear functional transformer expansion of the network inputs is initially performed and the resulting terms are linearly combined. The obtained structure has a good nonlinear approximation capability and the estimation of the network weights is linear [4]. Due to the linear estimation, the training of these networks is rapid, requires low computational effort and its convergence is guaranteed. In the present work a single Artificial Neural Network based on Functional-Link Network [FLN] has been developed to forecast the short-term electrical load. The accuracy of predicted load results was compared with the actual load data.

II. ARTIFICIAL NEURAL NETWORK BASED LOAD FORECASTING

Artificial Neural Networks are relatively crude electronic models based on the neural structure of the brain. The brain basically learns from experience. The biologically inspired methods of computing are thought to be the next major advancement in the computing industry. The fundamental processing element of a neural network is a neuron. The basic units of neural networks, the artificial neurons, simulate the four basic functions of natural neurons. Figure 1 shows a fundamental representation of an artificial neuron.

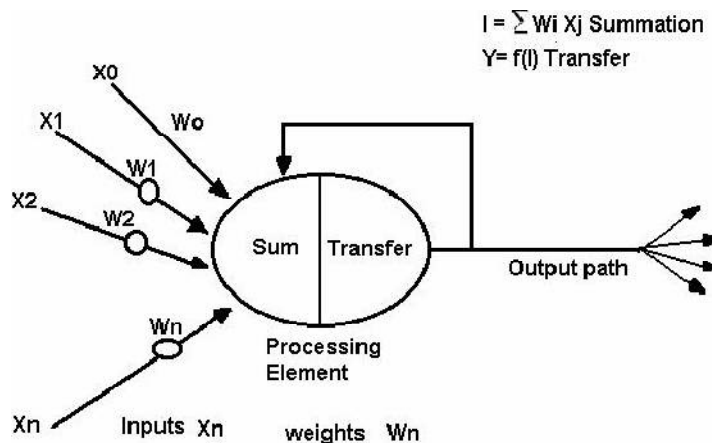


Fig.1 A Basic Artificial Neuron

In figure 1, various inputs to the network are represented by the mathematical symbol, $x(n)$. Each of these inputs is multiplied by a connection weight. These weights are represented by $w(n)$. In the simplest case, these products are simply summed, fed through a transfer function to generate a result, and then output. This process lends itself to physical implementation on a large scale in a small package.

III. 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 forecasts 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 was 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:

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

where

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

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

k : index for data length

W ; : the weight vector

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

day i

$$Y(i - 1) = [y(i - 1), y(i - 2), \dots, y(i - k)] =$$

In contrast to the conventional approaches, the nonlinear function is used with the weight vector to represent the load model. The weight vector W , can be thought of as the storage that contains a certain load pattern, and $F(., -)$ 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 , should be estimated using previous load data for each pattern. Weekdays are used to adjust the weight as follows:

To estimate the weekday load pattern for day i , three latest $y(i - 1) = F(i @ i, Y(i - 2))$, where the output data $y(i - 1)$ is the latest weekday load, the input data $Y(i - 2) = [y(i - 2), y(i - 3)]^*$ is the next two latest weekday loads and $i @ i$ 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: where $i d$ represents the previous type d day. For example, $j 1$ represents the previous Saturday when day i is a Saturday; yz for the previous 1st or 3rd Sunday; $j 3$ for the previous 2nd, 4th or 5th Sunday, etc. The weight vector is adjusted using equations according to the pattern in which the load t to be forecasted is included. The error backpropagation algorithm is used to decrease the error, for example, in the case of weekdays is minimized following the rule, 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: $\hat{y}(i) = F(i @ i, Y(i - 1))$, where $c(z)$ 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 forecasting's, and the resulting three models constitute the daily load forecasting as follows:

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

where $i @ i$ 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 $c(z)$ depends on the time band and contains 9, 10, or 5 hour data.

Method 2

Another important characteristic of load is shown in Fig. 2 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:

$$y(i, t) = F(W(i, t), y(i, t - 1), y(i, t - 2), \dots, y(i, t - m),$$

$$y(i - 1, t), y(i - 1, t - 1), \dots, y(i - 1, t - m),$$

$$y(i - n, t), y(i - n, t - 1), \dots, y(i - n, t - m)),$$

(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

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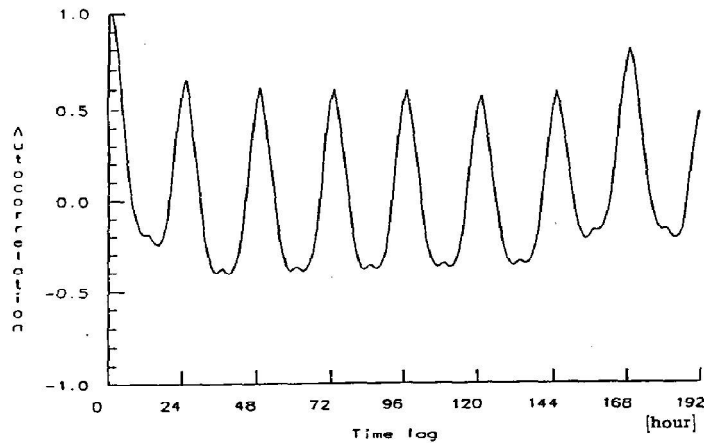


Fig. 5 Autocorrelation of hourly load

each time using previous load data for each pattern in a similar way as equations. 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:

$$y(2 - n, t), y(i - n, t - 1), \dots, y(i - n, t - m)$$

where $\hat{y}(2, t)$ indicates the load forecast at day i , time t .

Table.1 Comparison of the forecasting result by two methods

hour	Method 1		Method 2		Refer. [10]	
	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

Note that Method 2 has only one output while Method 1 has 24 outputs. This means there is less number of weights in Method 2. Since equation is for each time, total number of weights for 24-hour is about the same. However, Method

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2requires 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.

IV. 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 predeterminedtolerance. 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 utilityload 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.

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