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Short-Term Load Forecasting By Using ANN

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Abstract
Load forecasting play an impartment role in power system planning, operation and control. Short-term load forecasting is an important basis of the secure and economic operation in power systems. Accurate load forecasting is helpful to improve the security and economic effect of power systems and can reduce the cost of generation. Therefore, finding an appropriate load forecasting method to improve accuracy of forecasting has important application value. This paper explains the general theory of neural network and builds a short-term load forecasting method based on Artificial Neural Network.

Keyword: artificial neural network, feed forward neural network, power system

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INTRODUCTION
Short term load forecasting plays a key role for the economic and secure operation of power systems.[1] A Precise short term electrical load forecasting, results in cost savings and secure operational conditions allowing utilities to commit their production resources to optimize energy prices and exchange with vendors and clients. Basic operations such as unit commitment, hydro-thermal coordination, interchange evaluation, and security assessments require a reliable short term load forecast. Future introduction of different tariff periods will make load forecasting much more important, not only for large utilities, but also for medium and small ones. Load forecasting in a power system can normally be classified into the following categories:[2]

- Very short-term load forecasting of up to a few minutes ahead
- Short-Term load forecasting lead time from one hour to one month
- Medium-Term load Forecasting time interval one month to one year
- Long-term load forecasting of the power system peak load up to 10 years ahead.

Efforts have concentrated mainly on short term forecasting since it plays a vital role in optimum unit commitment, start up and shut down of thermal plants, control of spinning reserve and buying and selling of power in inter a connected system In this work, an approach for performing short-term load forecasting based on ANNs is proposed. Artificial neural networks (ANN), whose operation is based on certain known properties of biological neurons, comprise various architectures of highly interconnected processing elements that offer an alternative to conventional computing approaches. They respond in parallel to a set of inputs and are more concerned with transformations than algorithms and procedures. They can achieve complicated input-output mappings without explicit programming and extract relationships (both linear and nonlinear) between data sets presented during a learning process. ANNs are massively parallel, so that, in principle, they are able to respond with high speed. Furthermore, the redundancy of their inter connections ensures robustness and fault tolerance, and they can be designed to self-adapt and learn.[3,4].

In recent years, ANNs have been applied to many areas of power system analysis and control. These include load forecasting,[5] static and dynamic security assessment, dynamic load modeling, and alarm processing and fault diagnosis.[6] These applications take advantage of the powerful mapping ability of ANNs and their inherently parallel and distributed processing characteristics for performing ultra-high-speed computation.

The application of ANNs to short-term load forecasting has gained a lot of attention. In[7], Dillon et al. used adaptive pattern recognition and self-organizing techniques for short term load forecasting. Later, in[8], he used an adaptive neural network for short term load forecasting. The availability of historical load data on the utility databases makes this area highly suitable for ANN implementation. ANNs are able to learn the relationship among past, current, and future weather variables and loads combining both time series and regression approaches. As is the case with time series approach, the ANN traces previous load patterns and predicts (i.e. extrapolates) a load pattern using recent load data. It also can use weather information for modeling. The ANN is able to perform non-linear modeling and adaptation. It does not need assumption of any functional relationship between load and weather variables in advance. We can adapt the ANN by exposing it to new data. Their ability to outperform traditional methods especially during rapidly changing weather conditions and the short time required to their development, have made ANN based load forecasting models very attractive alternative for on line implementation in energy control centers.

In this paper, we demonstrate ANN capabilities in load forecasting with the use of load as an input. In addition, only temperature (dry bulb and dew point),energy PR, AGC, and spinning reserve variables are used here, in this application, where results show that other weather variables like sky condition (cloud cover) and wind velocity have no serious effect and may not be considered in the load forecasting procedure.

ARTIFICIAL NEURAL NETWORK

Recently, some nonlinear technologies develop rapidly, such as ANN which has powerful abilities of independent learning and nonlinear mapping. Because the changes of power load is affected seriously by many factors such as weather situation and social activities and lots of nonlinear mapping relations exist in it, it is meaningful to find out effective load forecast methods by introducing these theories.

ANN is a theoretical mathematics model about the brain and its activities. It consists of lots of processing units (nerve units). It is a mathematics model of the connection of nerve units and a large-scale nonlinear self-adapting. Abilities of computing, self-learning, self-adapting, nonlinear mapping and fine error correction make it be applied broadly in pattern recognition, image processing, signal and information processing, system optimizing and intelligent control. Applying ANN to load forecasting, especially short-term load forecasting, has notably effect, because ANN combines meteorological factor with change trend of load and then can forecast the maximum load of a day, gross load and hour load.

The development of an ANN based STLF model it is divided into two processes, the "learning phase" and the "recall phase". In learning phase, the neurons are trained using historical input/output data and adjustable weights are gradually optimized to minimize the difference between the computed and desired outputs. Corresponding pairs of the input and output values are designated as training vectors. The ANN allows outputs to be calculated based on some form of experience, rather than understanding the connection between input and output (or cause and effect).[9-11]

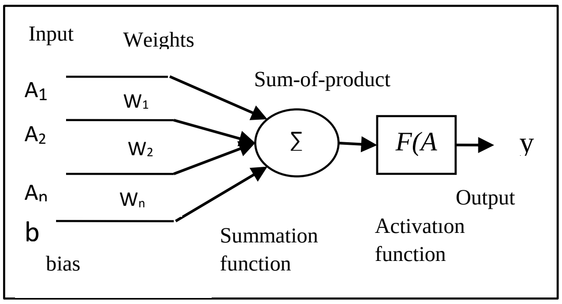

***Fig. 1** Basic Model of Artificial Neural Network.*

In recall phase the new input data is applied to the network and its outputs are computed and evaluated for testing purpose. In the ANN based STLF model, a layered ANN structure (Input layer, Hidden layer, and Output layer) is used. In neural network the weights are calculated by a learning process using error propagation in parallel distributed processing.

Feed-forward Network Model

A multi-layer feed-forward neural network can be used for STLF purposes. At present, multi-layered perception network trained by back propagation algorithm is the most popular neural network. The FNN is trained to approximate the nonlinear function *F* (.) between the hourly load and the input variables. In this FNN model nonlinear sigmoid function is used in hidden layer and linear sigmoid function is used in output layer. The feature of BP neural network model is that nerve units in a layer have connection only with adjacent layers, nerve units within a layer have no connection with each other, and nerve unites in different layers have no feedback connection. This model consists of three layer, such as input layer, hidden layer, and output layer. The number of inputs variables, neurons in the hidden layers, and output usually defines the FNN architecture. Figure 2 shows the architecture of FNN, in which number of inputs are 10, neurons in hidden layer are 60, and one output.

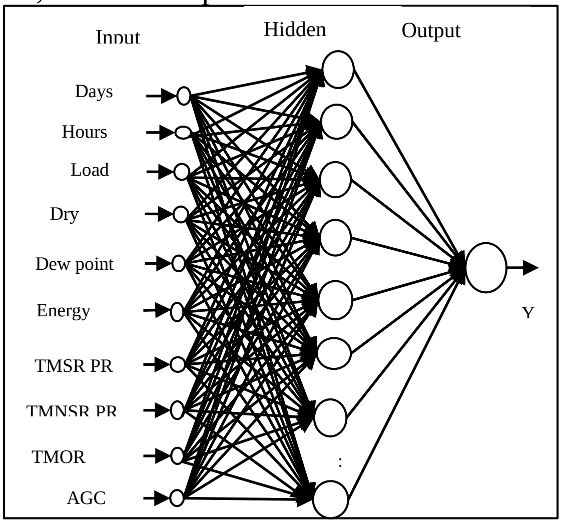

***Fig. 2** Feed-forward Neural Network Structure.*

Input Selection: The Selection of input variable is impartment in short term load forecasting. In this paper, data is used for training of two month 2000 (Jan. & Feb.) of UK based utility. In this data ten input variables are used such as days, time(hours), load, dry bulb temperature, Dew point temperature, energy PR(public relation), TMSR PR(ten minute spinning reserve PR), TMNSR PR (ten minute not spinning reserve PR), TMOR PR(ten minute off reserve), and AGC(automatic generation control). In this model the numbers of inputs are 10, hidden units are 60, and that output unit is 1.

Normalization/scaling: The activation functions of a neural network operate optimally in a small range. Hence there is need for normalization (scaling) of data. Load data were scaled such that they were within the range (0, 1). For this purpose the actual load was scaled using the following relationship.

$L_n = (L_a - L_{min})/(L_{max} - L_{min})$

Where,

L_a = the actual load

L_n = the scaled load which is used as input to the net

L_{max} = the maximum load

L_{min} = the minimum load

ANN Training: The data of one month, the year 2000, is used for training, testing and validation of the ANN, in which 70% for training, 15% for testing, and 15% used for validation. The ANN trained to be used at any time during the month. The network will be trained with Levenberg-Marquardt back propagation algorithm (trainlm), unless there is not enough memory, in which case scaled conjugate gradient back propagation (trainscg) will be used. Its performance is analysis by using mean square error and regression analysis. This optimization technique is more powerful than gradient descent, but requires more memory. The theory behind this approach is to adjust the ANN weights in the direction of minimizing the error between the desired and the ANN outputs.

SIMULATION AND RESULTS

The use of Levenberg-Marquard training algorithm resulted in a very fast training, and the error was significantly reduced within few iterations. Then, the performance of the developed ANN model for load profile forecasting was tested using windows of data that were not included in the training set. Table 1 shows the ANN output where it is compared to the actual load and forecasted load. For more accurate evaluation of the ANN's performance, the following absolute percentage error is used

APE=actual load (Y_i) -forecasted load ($\hat{Y}_i$)/

actual load (Y_i) *100 Eq. (1)

$$\text{MAPE}=\frac{1}{N}\sum_{i=1}^{N} APE \qquad \text{Eq. (2)}$$

Where, Eq. (1) gives the absolute percentage error at every testing point. However, an average of this absolute error over a period of time may be used for an overall evaluation and comparison with other techniques. The mean absolute percentage error is given by Eq. (2) where N is the number of testing points (i.e. N=24).

For the results shown in Table 1 a period of 24 hours (1 day), the mean average of the percentage error for the ANN forecasting is MAPE=0.8152.

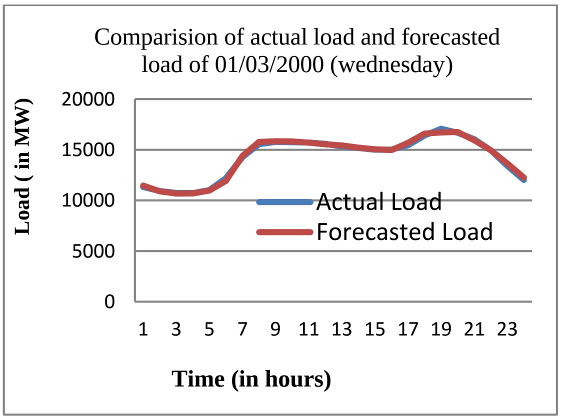

Fig. 3. *Comparison of MAPE (%) of Different Methods.*

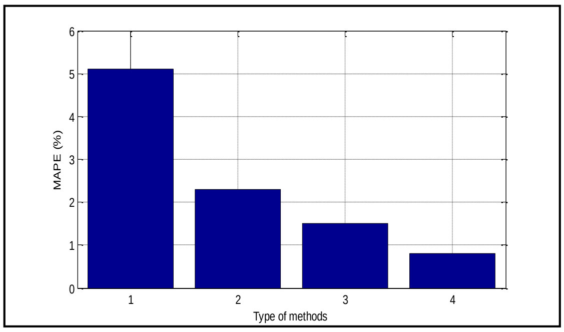

Fig. 4. *Comparison of Different Methods.*

In Figure 4 show the comparison of different methods, in this figure 1- regression method, 2- fuzzy logic, 3-fuzzy neural network, and 4- neural network.

Table 1. *Actual Load, Forecasted Load And Absolute Percentage Error of 24 Hours Load Forecasting.*

Time in (hours)	**Actual Load (Y_i)**	**Forecasted Load($\hat{Y}_i$)**	**APE (%)**
1	11314	11466	1.340
2	10919	10901	0.164
3	10732	10677	0.512
4	10712	10683	0.270
5	11012	10967	0.408
6	12186	11928	2.117
7	14272	14399	0.889
8	15559	15773	1.375
9	15773	15845	0.456
10	15737	15821	0.533
11	15718	15689	0.184
12	15581	15537	0.282
13	15325	15423	0.639
14	15182	15200	0.118
15	15000	15055	0.366
16	15023	14969	0.359
17	15440	15680	1.554
18	16411	16600	1.151
19	17076	16706	2.16
20	16683	16748	0.389
21	16045	15935	0.685
22	14958	14956	0.013
23	13413	13636	1.662
24	12022	12255	1.938
MAPE(%) = 0.8152			

CONCLUSION

The short-term load forecasting model is a critically important decision support tool for operating the electric power system securely and economically. Because of their input-output mapping ability, artificial neural networks are well suited for this type of applications, in this paper, an investigation on the use of ANN's for short term load forecasting for the US based power utility has been conducted.

A simple multi-layered feed forward ANN has been used and results show that the ANN is able to interpolate among the load and other variables pattern data of training sets to provide the future load pattern. However, these are preliminary results. The possibility for better results exists and can be achieved by using: 1) more advanced types of ANN, 2) better selection of input variables, 3) better ANN architecture, and 4) better selection of the training set.

FUTURE SCOPE

The future scope of load forecasting is very highly demandable in power utilities in India. STLF is the most deciding factor in bidding strategies, buying and selling of electricity, interchange evaluation, and tariff formulation.

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