Short-Term Load Forecasting by using Ann, Fuzzy Logic and Fuzzy Neural Network

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Abstract: **Electrical load forecasting plays an important role in planning, operation and control of power system. The accuracy and price forecasted value is necessary for economically efficient operation and effective control. Proper forecasting may result efficient generation and distribution and side by maintaining the sufficient security operation. Due to deregulation in an energy sector and the energy market, there is a pressing need of accurate STLF method. Accurate load forecasting is helpful to improve the security and economic effect of power systems and can reduce the cost of generation. Therefore, finding a fast and appropriate load forecasting method to improve accuracy of forecasting has important application value. This paper presents an investigation for the short term (one day to seven days) load forecasting of the load demand for the UK based Power utility, by using artificial neural network, fuzzy logic, and fuzzy neural network.**

In this paper, past data of UK based power utility is used in which independent variable such as dry bulb; wet bulb temperature, previous load, energy PR and TMSR (Ten minute spinning reserve) are mainly used.

Key word: Load Forecasting, Short-Term Load Forecasting (STLF), Artificial Neural Network, Fuzzy Logic, Fuzzy Neural Network,

I. INTRODUCTION

In order to meet power systems requirements continuously and having sustained economic growth, load forecast has become a very important task for electric power utilities. An accurate load forecast become more imperative in managing utility, developing a power supply strategy, finance planning and electricity market price management. In general, the required load forecasts can be classified into three categories short, medium and long term load forecasts. Short term load forecasting (half hour to one week ahead) represents a secure and economic operation of power systems. Medium term load forecasting (one week to several months) deals with the scheduling of fuel supplies and maintenance operations, and long term forecasting (more than a year ahead) is useful for planning operations.

To supply the load demand over a particular duration of time involves the start up and shutdown of entire generating units, which will be determined by a number of generation control functions such as hydro Scheduling, hydro-thermal coordination, economic dispatch, load management, operation scheduling unit commitment and interchange evaluation [1]. It is a main goal for any utilities to operate at the cost as low as possible. One way to achieve this is to minimize the forecast error. It was estimated that an increase of operating cost associated with a 1% increase of forecast error was 10 million pounds per year of British power utility system [2].

This paper is organized as follow: In section-II introduce basic theory of ANN; section-III represent Fuzzy logic, section-IV represent Fuzzy Neural Network, section-IV represent simulation and results of STLF, and section-VI represent the conclusion.

II. BASIC THEORY OF ARTIFICIAL NEURAL NETWORK

In this paper, the intelligence methods, such as Neural Network, Fuzzy Logic and Fuzzy Neural Network have been proposed and investigated for Short-Term Load Forecasting (load forecasting of one hour to one day). A Comparative study of these methods is also carried out and presented. The validity of proposed methods has been investigated using historical load data of ISO New England (an RTO) IPP, power utility.

1. Artificial Neural Network

Recently, some nonlinear technologies developed rapidly, such as ANN which have 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 relationship exist between them, 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. The development of an ANN based STLF model 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 past-experience, rather than understanding the connection between input and output (or cause and effect).

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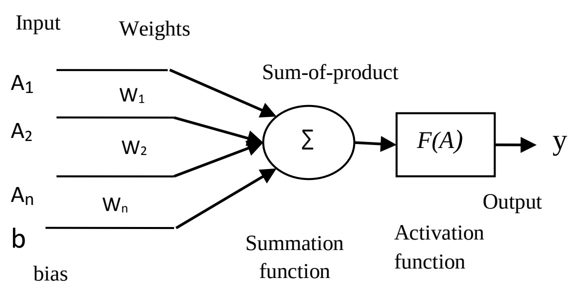

Fig. 1 Basic model of artificial neural network

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.

2. 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. Fig. 2 shows the architecture of FNN, in which number of inputs are 6, neurons in hidden layer are 80, and one output.

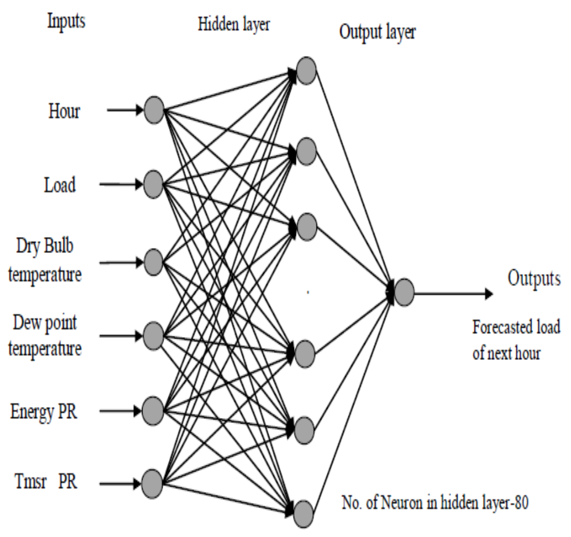

Fig 2 Architecture of feed forward neural network

Input selection: The Selection of input variable is impotent in short term load forecasting. In this model, data is used for training of two month Jan and Feb-2000 of UK based power utility. In this data six input variables are used such as time(hours), previous load, dry bulb temperature, Dew point temperature, energy PR(public relation), TMSR PR(ten minute spinning reserve PR), In this model the numbers neurons in hidden layer are 80, 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. For this purpose the input and output load data are scaled such that they are within the range (0, 1) 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 proposed method has been applied for short-term load forecasting of power utility of New England (an RTO), an independent, non-profit corporation. The network has been trained with data set of 1464, in which data set of 1024 is used for training and data set of 440 is used for testing and validation. After training, this trained model is used for short-term load forecasting.
After obtaining the forecasted results from simulation process, the forecasted values are compared with the actual values and the absolute percentage error (APE) is calculated for every hour using the following formula:

$$APE = \frac{L_{actual} - L_{forecasted}}{L_{actual}}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{L_{actual} - L_{forecasted}}{L_{actual}} * 100$$

Where,

L_{actual} = actual load of an hour
$L_{forecasted}$ = forecasted load of an hour

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N = number of hours (N=24)

Training performance is summarized in table- 1

Table- 1 Performance of trained ANN model

Parameters	Data	MSE	R
Train	1024	8.86180	0.998998
Validation	220	2.94331	0.996198
Testing	220	2.01806	0.997699

The regression R Values measures the correlation between outputs and targets. R value of 1 means a close relationship and 0 means a random relationship between outputs and targets. Mean Squared Error is the average squared difference between outputs and targets. Thus lower values are better. If the value of mean square error (MSE) is zero, it indicates zero error.

Table 2 shows the 24 hour ahead load of 01/03/ 2000 and Fig.3 shows the graphical representation of actual and forecasted load.

Table 2 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			

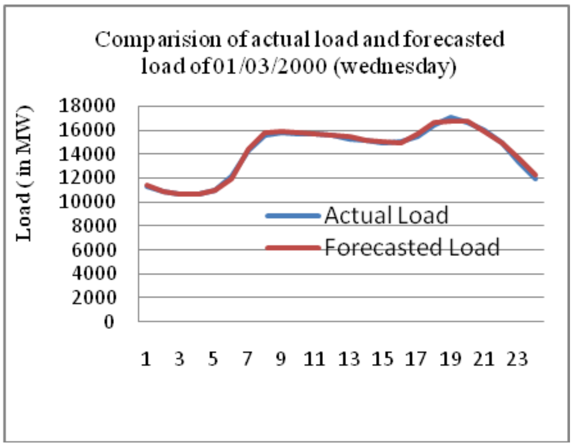

Fig. 3 Representation of actual load and forecasted load of 01/03/2000

This model is applied for one day to seven days ahead STLF. The results are shown in table 3.

Table 3. MAPE of different seven days using ANN

Date	Day	MAPE (%)
1/03/2000	Wednesday	0.815
2/03/2000	Thursday	0.654
3/03/2000	Friday	0.881
4/03/2000	Saturday	2.480
5/03/2000	Sunday	2.130
6/03/2000	Monday	1.560
7/03/2000	Tuesday	1.750

III. FUZZY LOGIC

A number of methods and techniques have already been used for prediction of load such Artificial Neural Networks (ANN), Regression Methods etc. Neural Networks are having the properties of slow convergence time and poor ability to process a large number of variables at a time. Fuzzy logic, on other side, gives a platform to represent and process data in linguistic terms, which makes the systems easily readable, understandable and operatable [8]. This is why; the Fuzzy Logic has been used to deal with the input parameters information after detailed analysis of data and knowledgebase (IF-THEN rules).

The load demand heavily depends on number of factors such as weather, day type, season etc. These factors actually decide the load to be forecasted depending on the conditions of these parameters on that day. Fuzzy logic is to extract a relation between electric load and the parameters affecting it. As accurate the parameters (weather, season or day type) are judged, accurate will be the load forecasted for the day. Fuzzy logic addresses such applications perfectly as it resembles human decision making with an ability to generate precise solutions from certain or approximate information.

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Fig 4 shows the configuration of fuzzy logic, which accepts crisp input and fuzzifier in imprecise data and vague statements such as low, very low, medium, high, very high, minimum, and maximum and provides decisions.

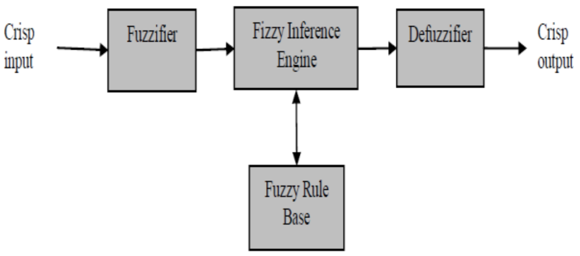

Fig 4. Basic configuration of fuzzy logic system

Fuzzy Set: Fuzzy logic starts with the concept of a fuzzy set. A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership [10].

Membership Function: The membership function is a graphical representation of the magnitude of participation of each input. It associates a weighting with each of the inputs that are processed, define functional overlap between inputs, and ultimately determines an output response. The rules use the input membership values as weighting factors to determine their influence on the fuzzy output sets of the final output conclusion.

Fuzzy Inference System: This is a major unit of a fuzzy logic system. The decision-making is an important part in the entire system. The FIS formulates suitable rules and based upon the rules the decision is made. This is mainly based on the concepts of the fuzzy set theory, fuzzy IF–THEN rules, and fuzzy reasoning. FIS uses “IF. . . THEN . . . statements, and the connectors present in the rule statement are “OR” or “AND” to make the necessary decision rules.

Defuzzification: The Defuzzification of the data into a crisp output is accomplished by combining the results of the inference process and then computing the "fuzzy centroid" of the area. The input for the defuzzification process is a fuzzy set (the aggregate output fuzzy set) and the output is a single number.

Proposed for STLF:
In this proposed method, a fuzzy inference system with Mamdani type has been applied for short-term load forecasting. The fuzzy inference process comprises of five parts: fuzzification of input variable, application of the fuzzy operator (AND or OR) in the antecedent, implication from the antecedent to the consequents across the rules, and defuzzification. In this method fuzzy logic toolbox software of MATLAB (version 7.6) is used [16]. Fig.4 shows the fuzzy inference system, which indicates input, output and fuzzy rule.

The first step of designing the fuzzy inference system is to decide which parameter affects the system performance. All these parameters must be taken as system input variable. The input variables are: previous load, dry bulb temperature, dew point temperature, energy PR, and ten minute spinning reserve (TMSR). All these input variables are first of all scaled / normalized in the required value limits.

The proposed method has been applied for determination of short-term load forecasting. The FIS model is design by using fuzzy logic toolbox MATLAB software. The proposed FIS model is used load data set of 1464. This FIS model is tested for one day ahead to seven day ahead load forecasting. The performance evaluation is done on the basis of mean absolute percentage error (MAPE).

IV. FUZZY NEURAL NETWORK

The proposed models possess adaptability to the changing data pattern which may occur in case the load demand pattern changes or the weather parameters change. ANN-based load forecasting gives large error when the weather profile changes very fast. ANN is slow in response to training provided to them. On the other hand, in a fuzzy inference system (FIS) when used for load forecasting, the design procedure is over dependent on designer’s experience and intuition, choice of input variables, linguistic variables, choice of input and output membership functions formulation of the rules. This causes the forecast procedure not to yield the best results in all cases.

APPROACHES FOR FUZZY NEURAL NETWORK (FNN):

In this approach, we adopt a fuzzy logic system (FLS) in the neural network, i.e., a fuzzy neural network as shown in Fig. 5.

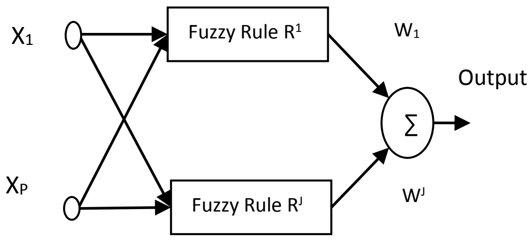

Fig. 5 Fuzzy neural network structure

The relation between the inputs and the output in the neural network’s hidden layer can be written as follow:

Fuzzy rule R^j:
IF (x_1 is A_1^j and (x_2 is A_2^j and ……. And (x_p is A_p^j)

THEN y is B^j
w_j = synaptic weights
p = input data dimension (p=1,2,…..6)
j = the number fuzzy rule (j= 1- 1024)
A_1^j = input
B_j = output
Where x is the p-dimensional input vector and y is the output. A_i^j is the label for the membership function

associated with the input variable x_i in Rule j. B^j is the label associated with the output variable y in Rule j. In Fig. 5, w_j is the synaptic weight from the hidden layer to the output layer.

Proposed For STLF:

The proposed method is used neuro-adaptive learning method, which works similarly to that of neural networks. Neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set. Fuzzy Logic Toolbox computes the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. The Fuzzy Logic Toolbox function that accomplishes this membership function parameter adjustment is called ANFIS [16**]**.

V. SIMULATION AND RESULTS

In this proposed method, ANFIS editor has been used for training, testing or checking of load data. Data of two month, i.e., Jan-Feb 2000 is used for training of SIMULINK model. The Hybrid optimization methods train the membership function parameters to emulate the training data. The training process stops whenever the maximum epoch number is reached or the training criteria for training. After training, the model is applied for testing or checking data of one day ahead to seven ahead STLF [15].

Table 3 MAPE of different days using Fuzzy Logic

Date	Day	MAPE (%)
1/03/2000	Wednesday	1.42
2/03/2000	Thursday	1.62
3/03/2000	Friday	1.92
4/03/2000	Saturday	2.23
5/03/2000	Sunday	2.54
6/03/2000	Monday	2.31
7/03/2000	Tuesday	1.82

Table 4 MAPE of different days using FNN model

Date	Day	MAPE (%)
1/03/2000	Wednesday	1.10
2/03/2000	Thursday	0.95
3/03/2000	Friday	1.34
4/03/2000	Saturday	2.10
5/03/2000	Sunday	2.64
6/03/2000	Monday	2.04
7/03/2000	Tuesday	1.15

The applicability of different methods for one day ahead STLF and seven days ahead STLF are summarized in Tables 5 and 6 respectively and their graphical representation are shown in Figures 5 and 6 respectively. From the tables and figures it can be observed that fuzzy logic, ANN and FNN methods are more accurate and reliable than traditional MLR method.

Table: 5 Comparison of MAPE of different STLF techniques

S. No.	Type of methods	MAPE (%)
1	Regression	4.50
2	Fuzzy logic	1.42
3	Fuzzy neural Network (FNN)	1.10
4	Artificial neural network (ANN)	0.81

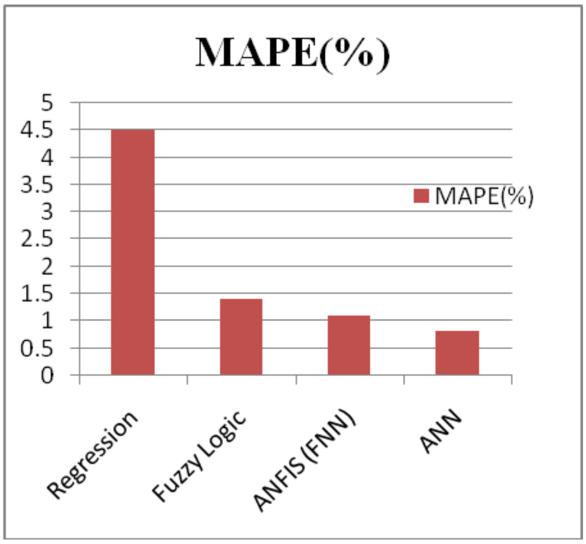

Fig. 5 Comparison of MAPE (%) of different STLF techniques of 01/03/2000

Table 6 Comparison of MAPE (%) of different STLF techniques of 01/03/2000

Days	ANN	FNN	FL	MLR
Wednesday	0.815	1.10	1.42	4.50
Thursday	0.654	0.95	1.62	4.83
Friday	0.881	1.34	1.98	4.99
Saturday	2.480	2.10	2.23	5.42
Sunday	2.130	2.64	2.54	5.76
Monday	1.560	2.04	2.31	5.84
Tuesday	1.750	2.15	1.82	6.21

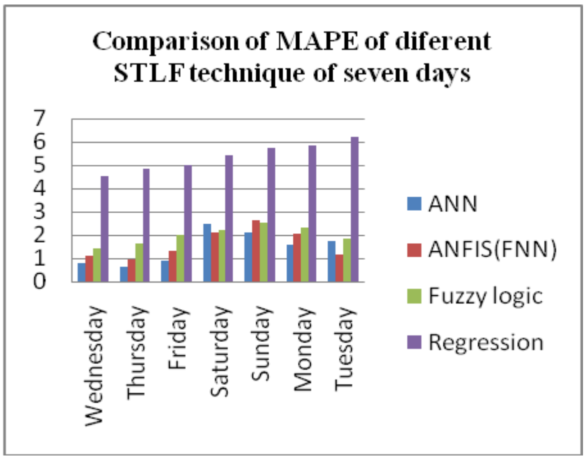

Fig. 6 Comparison of MAPE (%) of different STLF techniques for seven different days

VI. CONCLUSIONS

In this paper, the three different methods namely ANN, Fuzzy Logic and Fuzzy Neural Network have been proposed for STLF. In order to investigate the accuracy and reliability of these methods, load data of ISO New England power utility is used and their performance is compared with multiple linear regression method. From the tables and Figures it can be observed that fuzzy logic, ANN and FNN methods are more accurate and reliable than traditional MLR method.

It may also observed that all three methods are provides useful tool for accurate and reliable STLF, which can help the power utilities for taking important decision related to buying and selling of electricity, bidding strategies, tariff formulation, interchange evaluation, generation scheduling, hydro-thermal coordination, unit commitment, and economic dispatch etc.

FUTURE SCOPE AND RESEARCH DIRECTION

In India for long-term load forecasting, partial end use method and econometric method are used. However for short term load forecasting, standard methods are not generally used. Short-term load forecasting is generally done using past experience and past data. Therefore, this is a pressing need to develop accurate methods for Short-term load forecasting as it plays an impartment role in electricity price formulation. Inaccurate load forecast is directly affecting the economy of any power utility.

Some of the important future research directions can be:

- Combining weather and load forecasting for STLF
- Incorporating load forecasting into various decision support systems
- Electricity price forecasting
- Finding factor affecting elements of short-term load forecasting except weather factors.

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