FUZZY SET CLASSIFIED NEURAL NETWORK APPROACH FOR SHORT TERM LOAD FORECASTING

S.Saranya,
M.Phil Scholar,
Department of Computer Science & Application,
PGP College of Arts & Science,
Namakkal, Tamilnadu, India.

B. Vasumathi,
Assistant Professor,
Department of Computer Science & Application,
PGP College of Arts & Science,
Namakkal,Tamilnadu,India

M.Sakthivel,
Assistant Professor,
Department of Computer Science & Application,
PGP College of Arts & Science
Namakkal,Tamilnadu,India

Abstract: Load forecasting is an important component for power system energy management system. Forecasting means estimating active loads at various load buses ahead of actual load occurrence Training data is classified using Fuzzy Set Based Classification Method. Temperature data is classified into five fuzzy sets (Very Cold, Cold, Normal, Hot and Very Hot). Relative Humidity is classified into four fuzzy sets (Very Dry, Dry, Humid and Very Humid). Day Type is classified into four fuzzy sets (Post-Holiday, Weekday, Pre-Holiday and Holiday). So, depending upon the temperature, relative humidity and day type, data is classified into eighty classes. After the classification, the neural network is trained for various classes using the historical data. The multilayer neural network structure has been used and the training is imparted using back propagation algorithm. . In this article, a Fuzzy Set Classified Neural Network Approach for Short Term Load Forecasting is attempted and implemented using Matlab 6.5.

Keywords: Fuzzy Set Based Classification, Training of Neural Network, Short term load forecasting

I. INTRODUCTION

The utilities are required to provide reliable power to customers. In the design stages, utilities need to plan ahead for anticipated future load growth under different possible scenarios. Their decisions and designs can affect the gain or loss of crores of rupees for their companies/utilities as well as customer satisfaction and future economic growth in their area. Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasting helps an electric utility to make important decisions including decisions on sale, purchase, banking of power (with other companies or utilities of same state or the neighboring states) and generating electric power, load switching, and infrastructure development. For sale or purchase, short-term load forecasting is used and for banking, generally long-term load forecasting is used. Load forecasts are extremely important for energy suppliers, and other participants in electric energy generation, transmission, distribution, and markets.

With the recent trend of deregulation of electricity markets, STLF has gained more importance and greater challenges. In the market environment, precise forecasting is the basis of electrical energy trade and spot price establishment for the system to gain the minimum electricity purchasing cost. In the real-time dispatch operation, forecasting error causes more purchasing electricity cost or breaking-contract penalty cost to keep the electricity supply and consumption balance.

Hybrid Fuzzy Neural Approaches

Researchers have proposed several different ways to combine fuzzy logic with neural networks techniques in order to improve the overall forecasting performance. They are classified into five categories according to the method of combination:

- Fuzzy logic system at the output stage of the neural network forecaster to manipulate the output
- Fuzzy logic at the input stage of a neural network to preprocess the inputs
- Integrated fuzzy neural network to create a fuzzy rule base from the historical training data

- Separate fuzzy logic and neural network forecasters to forecast different components of the load
- Fuzzy logic technique for the classification of huge training data into different classes and neural network to forecast the load according to the classified training data.

II. EXISTING TECHNIQUES

a) Short Term Load Forecasting

Load forecasting plays an important role in power system planning, operation and control. Forecasting is the study to estimate active loads ahead of actual load occurrence. Planning and operational applications of load forecasting requires a certain 'lead time' also called forecasting intervals. Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. Load forecasts are extremely important for energy suppliers, and other participants in electric energy generation, transmission, distribution, and markets. The forecasts for different time horizons are important for different operations within a utility company.

b) Classification Of Load Forecasting Methods

In terms of lead time, load forecasting methods are divided into four main categories as listed below .

- Very short-term load forecasting
- Short-term load forecasting
- Mid-term load forecasting
- Long-term load forecasting

Short-term load forecasting can help to estimate load flows and to make decisions that can prevent overloading. Timely implementations of such decisions lead to the improvement of network reliability and to the reduced occurrences of equipment failures and blackouts. In the deregulated economy, decisions on capital expenditures based on long-term forecasting are also more important than in a non-deregulated economy when rate increases could be justified by capital expenditure projects.

Most of the forecasting methods use statistical techniques or artificial intelligence algorithms such as regression, neural networks, fuzzy logic and expert systems. Two of the methods, so-called end-use and econometric approach are broadly used for medium-and long-term forecasting. A variety of methods, which include the so-called similar day approach, various regression models, time series, neural networks, statistical learning algorithms, fuzzy logic, and expert systems, have been developed for short-term forecasting. As we see, a large variety of mathematical methods and ideas have been used for load forecasting. The development and improvements of appropriate mathematical tools will lead to the development of more accurate load forecasting techniques.

c) Factors Affecting System Load

The system load is the sum of all the consumers' load at the same time. The objective of system Load Forecasting is to forecast the future system load. Good understanding of the system characteristics helps to design reasonable forecasting models and select appropriate models in different situations. Various factors influence the system load behavior, which can be mainly classified into the following categories

- Weather
- Time
- Economy
- Random disturbance.

The effects of all these factors are introduced as follows to provide a basic understanding of the load characteristics.

III. THE PROPOSED TECHNIQUE

The hourly historical data of the weather conditions and the load are classified according to their characteristics and are used by the ANN to create a non-linear model for each class. These non-linear models are then used to forecast the short-term (hourly) loads. The classification of load data is accomplished by fuzzy set techniques.

The Figure 1 shows the block diagram representation of the proposed method. The inputs to the fuzzy set based classifier are hourly data of weather information i.e., Temperature and Relative Humidity and day type information. Pre-Holiday and Post-Holiday categories are made keeping in view that Holiday effect on load can be seen the days before and after the holiday. This classifier converts the data into various classes. Each class uses the training data of that particular class to train the neural network and produces system load as output depending upon the input set. Neural networks are trained using Back-propagation algorithm with Delta learning rule. A sigmoid transfer function is used in this method.

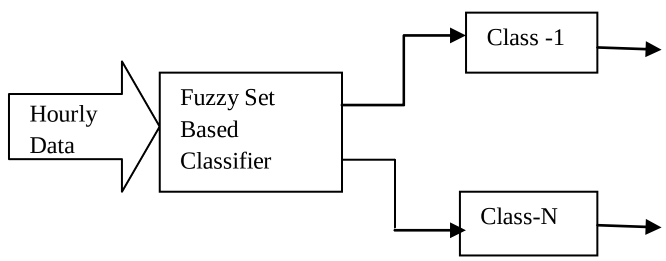

Figure 1: Block Diagram Representation of the Proposed Technique

a) Fuzzy Set Based Classification

Fuzzy logic technique is found to be most promising technique for classification of huge data. In the proposed methodology concepts of Fuzzy Logic set theory are used to classify the huge amount of historical data for Temperature, Relative Humidity and Day type. Temperature data is fuzzified into five main fuzzy sets described as

- Very Cold (VC),
- Cold (C),
- Normal (N),
- Hot (H) and
- Very Hot (VH).

Relative Humidity is fuzzified into four main fuzzy sets described as

- Very Dry (VD),
- Dry (D),
- Humid (H) and
- Very Humid (VH).

Day Type is fuzzified into four main fuzzy sets described as

- Post-Holiday (PostH),
- Weekday (WD),
- Pre-Holiday (PreH) and
- Holiday (H).

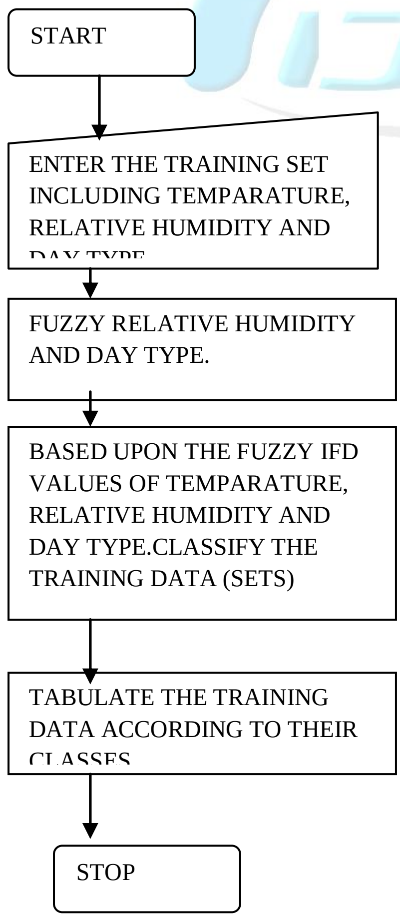

Figure 2: Flowchart for Data Classification

The categories of temperature, relative humidity and day type are then used to form eighty classes of weather conditions and day type information such as Very Cold-Very Dry-Post Holiday (VC-VD-PostH), Very Cold-Very Dry-Weekday (VC-VD-WD), Very Cold-Very Dry-Pre-Holiday (VC-VD-PreH), Very Cold-Very Dry-Holiday (VC-VD-H). The numbers from 1-80 are assigned to the eighty classes and shown in Table 1.

DAY TYPE		PostH	WD	PreH	H
TEMP.	RH				
VC	VD	1	2	3	4
VC	D	5	6	7	8
VC	Hu	9	10	11	12
VC	VHu	13	14	15	16
C	VD	17	18	19	20
C	D	21	22	23	24
C	Hu	25	26	27	28
C	VHu	29	30	31	32
N	VD	33	34	35	36
N	D	37	38	39	40
N	Hu	41	42	43	44
N	VHu	45	46	47	48
H	VD	49	50	51	52
H	D	53	54	55	56
H	Hu	57	58	59	60
H	VHu	61	62	63	64
VH	VD	65	66	67	68
VH	D	69	70	71	72
VH	Hu	73	74	75	76
VH	VHu	77	78	79	80

Table 1: Numbers Assigned to Various Classes

b) The Algorithm

The algorithm for the proposed technique is implemented in two parts namely data classification and training and load forecasting.

Algorithm for Data Classification

Training data preparation and classification based on fuzzy set based classification technique is the first part in the implementation of the technique.

Step 1: Enter the training set including temperature, relative humidity and day type.

Step 2: Fuzzify temperature, relative humidity and day type using their membership functions.

Step 3: Based upon the fuzzified values of temperature, relative

humidity and day type, classify the data (sets).
Step 4: Tabulate the data according to their classes and then stop.

Algorithm for Training And Load Forecasting

The second part of the implementation of the technique includes training of Neural Network to forecast hourly loads based upon the classified data. The algorithm steps are:-

Step 1: Enter the input vector set including weather information i.e., temperature, relative humidity and day type information.
Step 2: Based upon the weather information and day type information provided select the class form the training data.
Step 3: Using the training data of that class train the Neural Network using back-propagation algorithm and display the final weights. Back-propagation algorithm is discussed in appendix.
Step 4: Forecast the hourly load using these final weight matrices and input vector provided and then stop.

a) Load Forecasting For Post Holiday & Summer

In this case, hourly load for Himachal Pradesh State Electricity Board (HPSEB) is forecasted for a post-holiday & summer day i.e. Monday of Summer (April). Training data includes an input vector and corresponding target output. Input vector is of 14 bit string. It includes, first 5-bits defining hour of the day (e.g., 00001 for 1st hour, 00010 for 2nd hour of the day and so on), next 3-bits defining the day of the week (e.g., 001 for Monday, 010 for Tuesday and so on), next 2-bits defining normalized values of temperature of previous hour and forecasted temperature for the hour for which load is to be forecasted, next 2-bits defining normalized values of relative humidity of previous hour and forecasted relative humidity for the hour for which load is to be forecasted, next 2- bits defining normalized values of load of previous hour and similar hour. Target output is the normalized value of load of that hour. Training data used for this case (summer and post-holiday) is given in Table 2. The table includes temperature (^{0}C), relative humidity (%), class and load (MW) information.

IV. RESULTS AND DISCUSSIONS

Time (Hrs.)	7-Apr-08				21-Apr-08				28-Apr-08			
	Temp. (^{0}C)	R.H. %	Class	Load (MW)	Temp. (^{0}C)	R.H. %	Class	Load (MW)	Temp. (^{0}C)	R.H. %	Class	Load (MW)
1	21	52	53	591	22	32	49	621	22	32	49	620
2	20	53	53	578	21	36	53	610	21	36	53	611
3	19	57	37	576	20	38	53	599	20	38	53	600
4	18	62	37	585	18	59	37	603	19	43	37	598
5	16	68	41	583	17	60	37	599	19	46	37	596
6	16	70	41	657	17	62	37	666	19	45	37	662
7	15	73	41	812	22	47	53	736	22	47	53	732
8	15	74	41	884	24	42	53	757	24	42	53	750
9	19	62	37	857	28	41	69	730	28	41	69	728
10	22	53	53	814	30	46	69	722	31	36	69	719
11	25	44	53	773	33	32	65	696	33	32	65	697
12	28	35	69	747	33	29	65	691	35	28	65	692
13	31	28	65	745	33	30	65	684	37	22	65	688
14	32	27	65	708	34	25	65	667	38	16	65	669
15	32	25	65	683	35	23	65	658	38	17	65	656
16	32	25	65	687	33	23	65	668	37	16	65	670
17	32	25	65	669	31	26	65	657	37	17	65	658
18	32	26	65	662	35	18	65	628	35	18	65	625
19	30	29	65	651	30	18	65	587	30	18	65	590

20	27	36	53	729	28	27	65	643	28	27	65	640
21	24	42	53	749	23	32	49	687	27	32	49	681
22	23	46	53	685	25	33	49	632	25	33	49	633
23	22	48	53	652	26	43	53	638	25	37	53	642
24	21	49	53	666	23	37	53	626	23	37	53	631

Table 2: Training Data for Case-I (Summer and Post holiday)

For classification of training data, weather information (Temperature and Relative Humidity) and day type information is used. For above mentioned input string, Day type is Post Holiday (as day is Monday), temperature is High (as temperature is 22^0C) and on the basis of relative humidity, the weather for the hour is Very Dry (as percentage relative humidity is 32 %). So the class for the hour is Post Holiday – High – Very Dry. From the Table 2, the number assigned to this class of weather information and day type information is 49.

Similarly, class number for the hour for which the load is to be forecasted is found on the basis of the forecasted temperature and forecasted relative humidity and day type. For example, the above mentioned training data is to be used to train the neural network to forecast the load for first hour of 28-04-2008. Forecasted temperature and forecasted relative humidity are 22^0C (High) and 32 % (Very Dry) respectively. Day type for the day is Post-Holiday. So, the number assigned to this class is 49 as shown in Table 2. As the class for this hour is same as that of the training set mentioned above, so the above training set can be used to train the neural network.

The input string for training of neural network for the first hour of case-1 is as

{**0 0 0 0 1 0 0 1 0.21 0.22 0.51 0.32 0.636 0.638**}

This training data is for the first hour of Monday having previous hour temperature of 21^0C and forecasted temperature for the same hour equal to 22^0C. Relative humidity for previous hour is 51 % and forecasted relative humidity for same hour is 32 %. The load for previous hour is 636 MW and for similar hour is 638 MW. Corresponding target string for above input string is {**0.621**} i.e., the target load for the hour is 621 MW.

When the neural network is trained, its weight matrices are frozen and input string is applied to the trained neural network corresponding to the first hour of 28-04-2015 to forecast. This string is as
{**0 0 0 0 1 0 0 1 0.23 0.22 0.3 0.32 0.656 0.638**}

The corresponding output of neural network is{**0.620**}i.e., the forecasted load for the first hour of 28-04-2015 is 620 MW. Forecasted results for twenty four hours for case-I are shown in Table 3 for 28-04-2015. Figure 3 shows the graphical

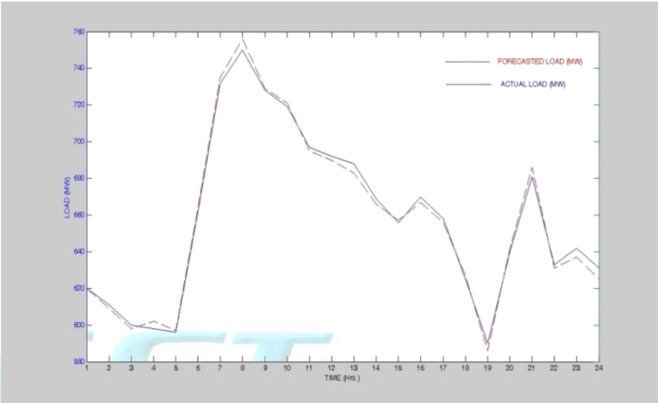

Figure 3: The Actual and Forecasted Loads for Monday 28-04-2015 (Summer and Post Holiday)

comparison of the actual and forecasted load. The forecasted load follows closely to the actual load. A maximum of -0.95% error is observed for this particular example.

V.CONCLUSIONS

A multi-layered feed-forward ANN combined with the fuzzy set-based classification technique for short-term electric load forecasting has been proposed in this thesis work. The hourly data was classified into classes based on the fuzzy set representation of two weather variables; temperature and relative humidity and day type information. The classification is based on the fact that the power system load is heavily influenced by the weather condition. The fuzzy set was used to assist the classification process in order to achieve the smooth transition between the classes of weather condition. After the classification, the neural network is trained for various classes by using the actual load data. For training, the supervised learning using BP algorithm is used for the training. The effectiveness is tested for summer and Post-Holiday

The forecasted load follows the actual load. Among all the cases a maximum of 4.86 % of error is observed, which can even be lowered if a large training data is used to train the neural network and industrial fluctuations are also considered while forecasting load for industrial feeders.

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