INTEGRATION OF FUZZY INFERENCE ENGINE WITH RADIAL BASIS FUNCTION NEURAL NETWORK FOR SHORT TERM LOAD FORECASTING

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ABSTRACT

This paper proposes a fuzzy inference based neural network for the forecasting of short term loads. The forecasting model is the integration of fuzzy inference engine and the neural network, known as Fuzzy Inference Neural Network (FINN). A FINN initially creates a rule base from existing historical load data. The parameters of the rule base are then tuned through a training process, so that the output of the FINN adequately matches the available historical load data. Results show that the FINN can forecast future loads with an accuracy comparable to that of neural networks, while its training is much faster than that of neural networks. Simulation results indicate that hybrid fuzzy neural network is one of the best candidates for the analysis and forecasting of electricity demand. Radial Basis Function Neural Network (RBFNN) integrated with Fuzzy Inference Engine has been used to create a Short Term Load Forecasting model.

Keywords: STLF, RBFNN ,Fuzzy Inference, Fuzzy Inference Neural Networks.

1 INTRODUCTION

Short term forecasts in particular have become increasingly important since the rise of the competitive market. Forecasting the power demand is an important task in power utility companies because accurate load forecasting results in an economic, reliable and secure power system operation and planning. Short Term Load Forecasting (STLF) is important for optimum operation planning of power generation facilities, as it affects both system reliability and fuel consumption. The complex dependence of load on human behaviour, social and special events & various environmental factors make load forecasting a tedious job. It is an important function performed by utilities for planning operation and control and is primarily used for economic load dispatch, daily operation and control, system security and assurance of reliable power supply. The impacts of globalization and deregulation demands improved quality at competitive prices, which is the reason why development of advanced tools and methods for planning, analysis, operation and control are needed. Important decisions depend on load forecast with lead times of minutes to months. The ability of ANN to outperform the traditional STLF methods, especially during rapidly changing weather conditions and the short time required for their development, have made ANN based STLF models a very attractive alternative for on line implementation in energy control centers. In this era of competitive power market, it is of main concern that how to improve accuracy of STLF.

In recent years use of intelligent techniques have increased noticeably. ANN and fuzzy systems are two powerful tools that can be used in prediction and modeling. Load forecasting techniques such as ANN [4], [5], [6], [7], [11], [15] , [18], Expert systems [14], fuzzy logic, fuzzy inference [2], [3], [10], [12], [13], [16] have been developed, showing more accurate and acceptable results as compared to conventional methods. A wide variety of conventional models for STLF have also been reported in the literature. They are based on various statistical methods such as regression [1], Box Jenkins models [9] and exponential smoothing [19]. Conventional ANN model based STLF have several drawbacks, such as long training time and slow convergent speed. The RBF model is a very simple and yet intrinsically powerfully network, which is widely used in many fields because of its extensive learning and highly computing speed [6],[7]. A neuro-fuzzy approach has been applied successfully in a price sensitive environment [2]. Soft Computing (SC) introduced by Lotfi Zadeh [20] is an innovative approach to construct computationally intelligent hybrid systems consisting of Artificial Neural Network (ANN), Fuzzy Logic (FL), approximate reasoning and optimization methods.

Fuzzy system is another research area which is receiving increased attention. The pioneering work of Zadeh in fuzzy set theory has inspired work in many research areas with excellent results. A fuzzy expert system for STLF is developed in [15]. It uses fuzzy set theory to model imprecision in the load temperature model and temperature forecasts as well as operator's heuristic rules. Fuzzy set theory proposed by Zadeh [20] provides a general way to deal with uncertainty, and express the subjective knowledge about a process in the form of linguistic IF-THEN rules.

Fuzzy Systems exhibit complementary characteristics, offering a very powerful framework for approximate reasoning as it attempts to model the human reasoning process at a cognitive level. It acquires knowledge from domain experts and this is encoded within the algorithm in terms of the set of If-Then rules. Fuzzy systems employ this rule based approach and interpolative reasoning to respond to new inputs. Fuzzy systems are suitable for dealing with problems caused by uncertainty, inexactitude and noise, so the uniting of fuzzy system and neural networks can exert respective advantages.

In this paper, a fuzzy inference neural network is presented to improve the performance of STLF in electric power systems. A Fuzzy Inference Neural Network initially creates a fuzzy rule base from existing historical load data. The parameters of the rule base are then tuned through a training process so that the output of the network adequately matches the available historical load data. The fuzzy system combines the fuzzy inference principles with neural network structure and the learning ability into an integrated neural network based fuzzy decision system. Combining the specific characteristic that the variety of power systems load is non-linear, we set up a new short-term load forecasting model based on fuzzy neural networks and fuzzy getting smaller inference algorithm. The flexibility of the fuzzy logic approach, offering a logical set of IF-THEN rules, which could be easily understood by an operator, might be a good solution for easy practical implementation and usage of STLF models. The hybrid FNN approach is finally used to forecast loads with greater accuracy than the conventional approaches when used on a stand- alone mode.

2 RADIAL BASIS FUNCTION NEURAL NETWORK

Radial Basis Function (RBF) Network consists of two layers, a hidden layer with nonlinear neurons and an output layer with linear neurons. Thus, the transformation from the input space to the hidden unit space is non-linear whereas the transformation from the hidden unit space to the output space is linear. The basis functions in the hidden layer produce a localized response to the input i.e. each hidden unit has a localized receptive field. RBFNNs exhibit a good approximation and learning ability and are easier to train and generally converge very fast. It uses a linear transfer function for the output units and Gaussian function (radial basis function) for the hidden units. The transform function of hidden layer is a non-negative and nonlinear function. In RBF neural network, three parameters are needed to study: the center and the variance of the basis function and the weight connecting hidden layer to the output layer. The RBF network has many study methods according to the different methods of selecting the center. In this paper, a method of the self-organizing study selecting RBF center is adopted. The method consists of two-step procedure: the first one is self-organizing study, which is to study the basis function center and variance; then the next step is supervisory study, which is the weight connecting hidden layer to the output layer. A RBF neural network embodies both the features of an unsupervised learning based classification and a supervised learning layer. The network is mainly a feed forward neural network. The hidden unit consists of a function called the radial basis function, which is similar to the Gaussian Density function whose output is given by

$$o_i = \exp\left(-\sum_{j=1}^{r} \frac{(x_{jp} - W_{ij})^2}{\sigma}\right) \quad (1)$$

where,

W_{ij} = Center of the ith RBF unit for input variable j

σ = Spread of the RBF unit

x = jth variable of the input pattern

The RBF neural network generalizes on the basis of pattern matching. The different patterns are stored in a network in form of cluster centers of the neurons of the hidden units. The number of neuron, determines the number of cluster centers that are stored in the network. The response of particular hidden layer node is maximum (i.e. 1) when the incoming pattern matches the cluster center of the neuron perfectly and the response decays monotonically as the input patterns mismatches the cluster center; the rate of decay can be small or large depending on the value of the spread. Neurons with large spread will generalize more, as it will be giving same responses (closer to 1) even for the wide variation in the input pattern and the cluster centers whereas a small spread will reduce the generalization property and work as a memory. Therefore, spread is an important parameter and depends on the nature of input pattern space.

The output linear layer simply acts as an optimal combiner of the hidden layer neuron responses. The weights 'w' for this layer are found by multiple linear regression technique. The output of the linear layer is given by

$$y_{mp} = \sum_{i=1}^{N} w_{mi}\, o_i + b_i \qquad (2)$$

where,

N = number of hidden layer nodes (RBF units)

y_{mp} = output value of the mth node in the output layer for the ith incoming pattern

w_{mi} = weight between ith RBF unit and mth output node

b_l = biasing strength of the mth output node

o_i = ith input to the linear layer.

The values of the different parameters of the RBF networks are determined during training. These parameters are spread, cluster centers, and weights and biases of the linear layer. The number of neurons for the network and spread is determined through experimentation with a large number of combinations of spread and number of neuron. The best combination is one which produces minimum Sum Squared Error (SSE) on the testing data.

3 FUZZY INFERENCE

Fuzzy inference is the process of formulating the mapping from a given input to the output using fuzzy logic. This process numerically evaluates the information embedded in the fuzzy rule base. The fuzzy rule base consists of "IF-THEN" type rules. For a set of input variables, there will be fuzzy membership in several fuzzy input variables. By using the fuzzy inference mechanism, the information is processed to evaluate the actual value from the fuzzy rule base. A good precision can be achieved by applying appropriate membership definitions along with well-defined membership functions. This is an information processing system that draws conclusions based on given conditions or evidences. A fuzzy inference engine is an inference engine using fuzzy variables. Fuzzy inference refers to a fuzzy IF-THEN structure. The fact that fuzzy inference engines evaluates all the rules simultaneously and do not search for matching antecedents on a decision tree makes them perfect candidates for parallel processing computers.

A fuzzy set is a set without a crisp, clearly defined boundary, and can contain fuzzy variables with a partial degree of membership, which is presented by the membership functions within the range. There are two types of fuzzy models. The first kind is known as Mamdani model [8]. In this model, both fuzzy premise part and consequence part are represented in linguistic terms. The other kind is Takagi-Sugeno model [17] that uses linguistic term only for the fuzzy premise part. In this paper the Takagi-Sugeno reasoning method is used.

The *fuzzification interface* is a mapping from the observed non-fuzzy input space $U \subseteq R^n$ to the fuzzy sets defined in U. Hence, the fuzzification interface provides a link between the non-fuzzy outside world and the fuzzy system framework. The *fuzzy rule base* is a set of linguistic rules or conditional statements in the form of: "IF a set of conditions is satisfied, THEN a set of consequences are inferred". The *fuzzy inference engine* is a decision making logic performing the inference operations of the fuzzy rules. Based on the fuzzy IF-THEN rules in the fuzzy rule base and the compositional rule of inference [14], the appropriate fuzzy sets are inferred in the output space.

Supposing the mapping μ_A from discussed region U to the range [0, 1]: $U \rightarrow [0,1]$, $x \rightarrow \mu_A(x)$ confirms a fuzzy subset of U, named A, the mapping $\mu_A(x)$ is known as membership function of A. The size of the mapping $\mu_A(x)$ shows the membership degree of x to fuzzy set A, which is called membership degree for short. In practice, membership function can be selected according to the characteristic of the object.

Fuzzy inference based on fuzzy estimation is a method by which a new and approximate fuzzy estimation conclusion is inferred using fuzzy language rule. This paper adopts composite fuzzy inference method, which is inference method based on fuzzy relation composing principle. A fuzzy inference engine can process mixed data. Input data received from the external world is analyzed for its validity before it is propagated into a fuzzy inference engine. The capability of processing mixed data is based on the membership function concept by which all the input data are eventually transformed into the same unit before the inference computations. A fuzzy inference engine normally includes several antecedent fuzzy variables. If the number of antecedent variables is k then there will be k information collected from the external world. Fuzzification and normalization are the two typical transformations. Another important property is that when an input data set is partially ambiguous or unacceptable, a fuzzy inference engine may still produce reasonable answers.

4 FUZZY INFERENCE NEURAL NETWORK

A fuzzy Inference neural network approach, which combines the important features of ANN and fuzzy using inference mechanism is proposed .This architecture is suggested for realizing cascaded fuzzy inference system and neural network modules, which are used as building blocks for constructing a load forecasting system. The fuzzy membership values of load and temperature are the inputs to the ANN, and the output comprises the membership value of the predicted load. To deal with the linguistic values such as high, low, and medium, architecture of ANN that can handle fuzzy input vectors is propounded. Each input variable is converted into a fuzzy membership function in the range [0-1] that corresponds to the degree to which the input belongs to a linguistic class. RBFNN has been integrated with fuzzy inference to form a FINN for Short Term Load Forecasting. The RBFNN is used to extract the features of input and output variables. It is noteworthy that the input variables are extended to include a output variable and extract the relationship between inputs.

4.1 Input Variable Selection and Data Processing

The most important work in building our Short Term Load Forecasting (STLF) models is the selection of the input variables. It mainly depends on experience and is carried out almost entirely by trial and error. However, some statistical analysis can be very helpful in determining the variables, which have significant influence on the system load. Normally more input neurons make the performance of the neural network worse in many circumstances. Optimal input parameters would result in a compact ANN with higher accuracy and also at the same time with good convergence speed. Parameters with effect on hourly load can be categorized into day type, historical load data and weather information. Temperature is the most effective weather information on hourly load. Data has been taken for Trans Alta Canada System.

In order to make minimum inference case, the input load is sorted into 5 categories and labeled as low (L), low medium (LM), medium (M), medium high (MH) and high (H). The input temperature is also sorted into 5 categories same as above. Design data consists of hourly data, integrated load data and temperature of two places. Keeping in view the large geographical spread of the data , for which the utility supply, the hourly temperature of two places have been taken in the historical data. Firstly data are normalized. The n rows thus give for each group the value of m feature denoting the characteristics of these groups. In the present work features correspond to characterization of data model i.e. hrs., two hours before load, one hour before load, temp.1, temp.2 In this paper, fuzzy IF-THEN rules of the form suggested by Takagi- Sugeno [19] are employed, where fuzzy sets are involved only in the premise part of the rules while the consequent part is described by a non-fuzzy function of the input variables. The historical data is used to design data which are further fuzzified using IF-THEN rule.

The data model involves the range of data low (L), low medium (LM), medium (M), medium high (MH) and high (H), five linguistic variables for each crisp data type. These five linguistic value are defined as L(3800 MW-4200 MW), LM (4280.001MW- 4760 MW), M(4760.001 MW-5240 MW), MH (5240.001 MW -5720 MW) and H(5720.001 MW-6200 MW)and the linguistic values for temperature are as L (-370°C to -230 °C), LM (-229.999°Cto -90°C), M(-89.999°C to +50°C), MH (+50.001°C to +190 °C) and H (+190.001°C to

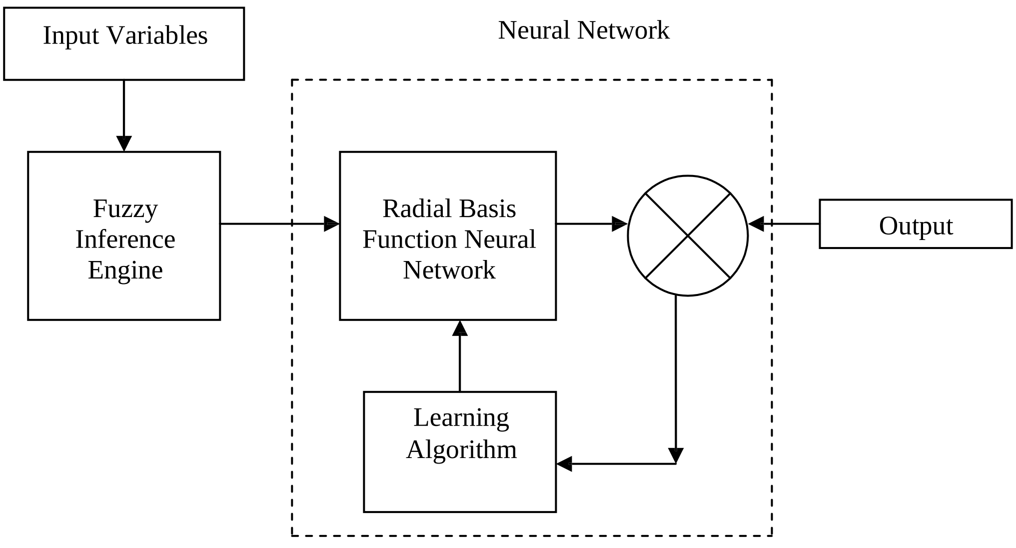

Figure 1: Forecasting Model

+330°C), using IF-THEN rule. These data are normalized and fuzzified using inference engine as shown in demand table (Table-1). The five linguistic variables using IF-THEN rule for load as well as temperature are as follows.

If P1 is low (L) and P2 is low (L) then α=LL

If P1 is low (L) and P2 is low medium (LM) then α=LLM
If P1 is low (L) and P2 is medium (LM) then α=LM
If P1 is low (L) and P2 is medium high (MH) then α=LMH
If P1 is low (L) and P2 is high (H) then α=LH
If P1 is low medium (LM) and P2 is low (L) then α=LML
If P1 is low medium (LM) and P2 is low medium (LM) then α=LMLM and so on.

4.2 Forecasting Model

In FINN the RBFNN plays an important role to classify input data into some clusters while the fuzzy inference engine handles the extraction of rules. Fig. 1 shows the structure of FINN that has two layers; input/output and rule layers. The input/output layer has input and output node. The input nodes of the input/output layer are connected to neurons on the topological map of the rule layer. The fuzzy membership neural networks are assigned to the weight between the input nodes and rule layer. Also, the consequent constant is assigned between the output node and rule layer. The parameter selection method can be considered as a rule base initialization process. Essentially, it performs a fuzzification of the selected input points within the premise space. The mean values of the memberships are centered directly at these points, while the membership deviations reflect the degree of fuzzification and are selected in such a way that a prescribed degree of overlapping exists between successive memberships. The fact that the initial parameters of the FINN are not randomly chosen as in neural networks but are assigned reasonable values with physical meaning gives the training of an FNN a drastic speed advantage over neural networks.

With fusing the strongpoint of fuzzy logic and neural networks, a fuzzy inference neural networks model, which effectively makes use of their advantages, has been developed. The training patterns for the ANN models are obtained from the historical loads by classifying the load patterns according to the day-types of the special days and linearly scaling the load values. The block diagram of the proposed system and the flow chart of the forecasting process are shown in the Fig.1. and Fig.2.

5 SIMULATION RESULTS

The most widely used index for testing the performance of forecasters is the MAPE. The

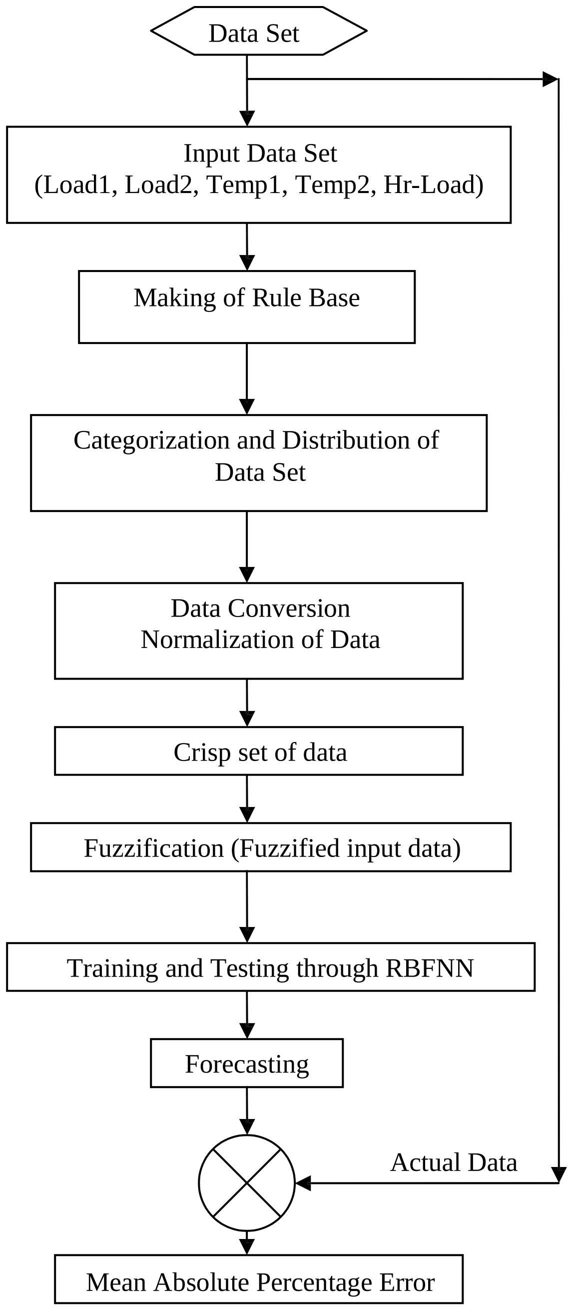

Figure 2: Flow chart of Forecasting Process

Table 1: Demand table

α (P1 \ P2)	L	LM	M	MH	H
L	LL	LLM	LM	LMH	LH
LM	LML	LMLM	LMM	LMMH	LMH*
M	ML	MLM	MM	MMH	MH
MH	MHL	MHLM	MHM	MHMH	MHH
H	HL	HLM	HM	HMH	HH

Table 2: Forecast errors in MAPE on seasonal transition weeks

Day	Winter January 25-31		Spring May 17-23		Summer July 19-25		Average	
	Day Ahead	**Week Ahead**	**Day Ahead**	**Week Ahead**	**Day Ahead**	**Week Ahead**	**Day Ahead**	**Week Ahead**
Monday	2.5711	2.5711	1.9990	1.9990	2.2050	2.2050	2.2584	2.2584
Tuesday	1.6763	1.5041	1.8121	1.8797	2.0467	1.9221	1.8450	1.7686
Wednesday	2.0342	2.0527	2.0369	1.9750	2.4277	1.9505	2.1663	1.9927
Thursday	2.4767	2.6438	2.2687	2.0208	1.5584	1.5206	2.1013	2.0617
Friday	2.9492	1.9225	1.8399	1.8356	1.5065	1.5079	2.0985	1.7553
Saturday	2.4953	2.3185	2.4913	2.3826	1.9120	1.9915	2.2995	2.2309
Sunday	2.7416	2.8998	2.6638	2.6110	1.6234	1.5122	2.3429	2.3410
Average	2.4206	2.2732	2.1588	2.1005	1.8971	1.8014	2.1588	2.0584

Table 3: Comparison with MLR and simple RBFNN

Day	Winter January 25-31			Spring May 17-23			Summer July 19-25		
	MLR	**RBFNN**	**FINN**	**MLR**	**RBFNN**	**FINN**	**MLR**	**RBFNN**	**FINN**
Monday	2.3863	1.0776	2.5711	2.7664	1.0856	1.9990	2.8015	1.2466	2.2050
Tuesday	1.6070	1.0727	1.5041	2.8966	0.7082	1.8797	2.2284	2.2017	1.9221
Wednesday	2.2656	1.1105	2.0527	3.3757	0.9606	1.9750	2.6688	0.8057	1.9505
Thursday	1.8675	0.7494	2.6438	2.3315	2.2876	2.0208	3.0628	1.2365	1.5206
Friday	1.6801	1.1171	1.9225	2.9397	1.1114	1.8356	2.6345	0.9062	1.5079
Saturday	2.8921	1.6459	2.3185	1.0263	0.7726	2.3826	2.4133	1.0312	1.9915
Sunday	2.3560	1.5838	2.8998	2.2336	1.7412	2.6110	2.1984	1.1475	1.5122
Average	2.3228	1.1939	2.2732	2.5100	1.2310	2.1005	2.5725	1.2246	1.8014

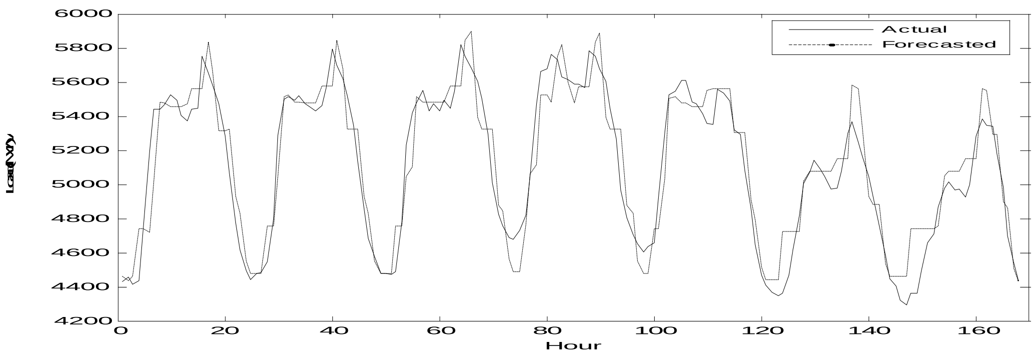

Figure 3: Forecast for Winter (January 25-31)

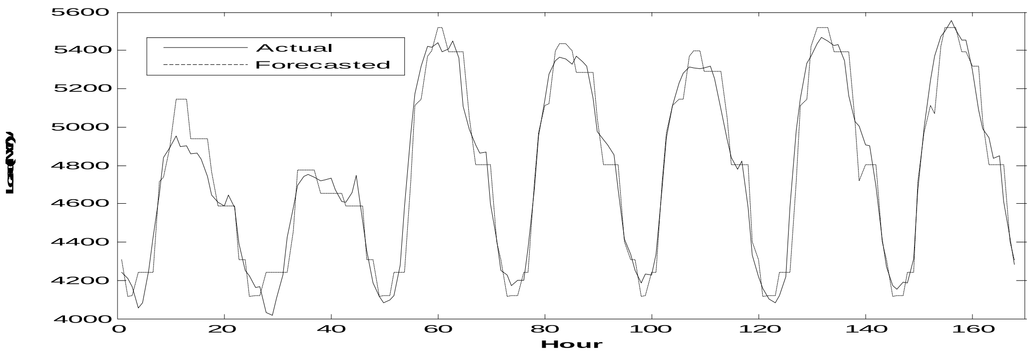

Figure 4: Forecast for Summer (July 19-25)

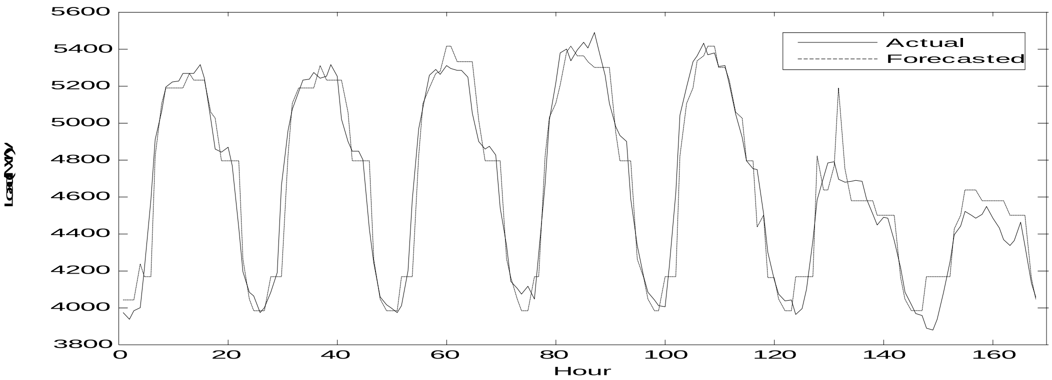

Figure 5: Forecast for Spring (May 17-23)

designed network is used to forecast the day ahead and week ahead forecast on an hourly basis. Forecasting has been done on the one year load data of Trans Alta Electric Utility for Alberta, Canada. Load varies from 3900 MW to 6200MW. The FINN is trained using last four weeks hourly load data and then they are used to forecast the load for the next 168 hours i.e. one week. The results are reported for three weeks, one each for winter, spring and summer seasons. This reflects the behaviour of the network during seasonal changes and corresponding results are shown in Table 2. It is observed that the performance of the day ahead and week ahead forecast are equally good. Load shape curves for three weeks are shown in Fig. 3, Fig. 4 and Fig. 5.The errors are tabulated in Table 2. It is observed from the figures that the forecaster captures the load shape quite accurately and the forecasting error on most of the week days are low with slightly higher error on weekend days.

For having a comparative study the proposed FINN method is compared with other two methods, conventional Multi Layer Regression and RBF neural networks for the same period of time. The result (Table 3) shows that the average MAPE for FINN is better than MLR in all seasons and the average MAPE for RBFNN is even better than FINN. But at the same time it is also noticeable that the training time required in the forecasting through RBFNN integrated with Fuzzy Inference is approximately ten times less than the training time required for simple RBFNN.

6 CONCLUSION

The benefit of the proposed structure is to utilize the advantages of both, i.e. the generalization capability of ANN and the ability of fuzzy inference for handling uncertain problems and formalizing the experience and knowledge of the forecasters. Load forecasting method proposed above is feasible and effective. A comparative study shows that FINN and RBFNN are more accurate as compared to MLR. The error depends on many factors such as homogeneity in data, network parameters, choice of model and the type of solution. The flexibility of the fuzzy logic offering a logical set of IF-THEN rules, which could be easily understood by an operator, will be a good solution for practical implementation. FINN training time was much faster and also effectively incorporated linguistic IF-THEN rules. Load forecasting results show that FINN is equally good for week ahead and day ahead forecasting and requires lesser training time as compared to other forecasting techniques, conventional regression MLR and simple RBF neural network.

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