A NOVEL HYBRID APPROACH TO SHORT TERM LOAD FORECASTING

Ashish Kumar SRIVASTAVA [1], Tariqul ISLAM [2]

[1]Jamia Millia Islamia (Central University), Electrical Engineering Department, New Delhi, India
[2]Jamia Millia Islamia (Central University), Electrical Engineering Department, New Delhi, India
chandraashish98@yahoo.in, tariq940@rediffmail.com

Abstract: *The knowledge of a day ahead load is necessary for a utility in a competitive electricity market for fuel purchase scheduling, planning for energy transactions and to maintain their power reserve close to the minimum as required by Independent System Operator. Previous researches do not consider the effect of wind direction on load forecasting, however this paper investigates the effect of wind direction and weather event on load requirements and accordingly presents a novel Neuro-Fuzzy based approach to Short term load forecast (STLF) i.e. a day ahead average load forecast utilizing parameters identified as historical load, temperature, weather event (for e.g. fog and snow) and wind direction. Four different input structures, three using Neuro-Fuzzy approach and one using only Neural network (NN) are tested. Among the four input structures, structure utilizing Neuro-Fuzzy approach with wind direction as one of the input parameters gives impressive result, with an average error of 1.735 %. The model is trained and tested on load and weather data pertaining to Norwalk/Stamford in Connecticut Valley Electric Exchange.*

Keywords: *Artificial Neural Network (ANN), Neural network (NN), Short term load forecasting (STLF), Multi Layer Perceptron (MLP), Simulation.*

1. Introduction

The objective of the power utility is to generate electric power according to the consumers demand of energy at all times and at minimum cost. This objective is achieved by advance knowledge of customer's load requirement. Load forecasts are categorized into long term, medium term and short term forecasts. Long term forecasts are made for one to several years ahead, medium term forecasts are made for one to several months ahead and short term load forecasts (STLF) are made for a lead time ranging from an hour to several days out. STLF is required for unit commitment, load dispatch, energy transfer scheduling of power system and also as inputs to load flow study and contingency analysis [11]. The accuracy of STLF has a significant impact on electric utilities operational efficiency.

The knowledge of a day ahead average load which is a form of STLF, is necessary for a utility in a competitive electricity market for fuel purchase scheduling, economic scheduling of generating capacity, planning for energy transactions and to maintain their power reserve close to the minimum as required by Independent System Operator [20]. Load forecast is made by extrapolating the past load behavior while taking into consideration the effect of other influencing factors such as weather event and day of the week [12]. The relationship between load and these factors is complex and nonlinear. In recent past, several classical techniques have been proposed and applied to the load forecasting. These classical techniques include linear regression models, moving average and exponential smoothing methods, stochastic process, data mining approach, autoregressive and moving averages (ARMA) models, Box-Jenkins methods and Kalman filtering base methods [2]-[8]. The classical techniques are based on linear analysis while relationship between load and weather variables is nonlinear which makes accurate modeling of the correlation very difficult using classical techniques[12], [19].

In recent years, Artificial neural network (ANN) has been successfully applied to STLF [1], [9]-[12], [15], [22]. It has the ability to deal with nonlinear relationship between input and output vectors. Neural network (NN) is a massively parallel distributed processor made up of simple processing units called artificial neurons which stores experimental knowledge through a learning process and making it available for use. The ANN learns by modifying the synaptic weights between neurons by comparing the output of the ANN to the actual output [24]. During learning, training sets i.e. known inputs (e.g. past load and

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temperature data) and output (e.g. forecast load data) pairs are applied to the NN and a mapping is constructed between various inputs and output load. This trained NN is able to generalize among the training sets and produce a corresponding output when presented with a novel input. Although, ANN based methods give better forecast results than classical techniques however they make use only of numerical data and fail to deal with human reasoning and qualitative inputs. Another artificial intelligence technique, Fuzzy logic is developed to form natural bridge between quantitative and qualitative world. Fuzzy logic is motivated not only to work in quantitative and numeric domains but also in qualitative domain because vague concepts are often described qualitatively by words. The accuracy of forecast model depends upon interrelationships of important parameters (weather etc.) that are themselves intrinsically uncertain and falls in qualitative domain. Fuzzy logic can be used effectively to handle these uncertainties. Neural networks and fuzzy systems each have their own shortcomings. While designing with the neural networks alone, the network is a black box that needs to be defined. This is highly compute-intensive process. Fuzzy systems on the other hand, require thorough understanding of the fuzzy variables and membership functions of the input-output relationships as well as good judgment to select the fuzzy rules that contribute most to the solution of the application. In order to overcome the shortcomings of both and to improve the accuracy of forecast, hybrid architecture comprising neural network and fuzzy system is suggested in present work which aims to combine the good features of both to overcome the limitations of each [13], [14], [16], [17], [21].

The load has to exhibit a strong degree of statistical correlation with input variables and appropriate inputs should be selected to represent all the external factors influencing the system load [15]. Different schemes have been developed to model anomalous and regular days [1], [11], [12], [19], [20]. Park *et al*. [1] and Paull *et al*. [21] emphasized that there is strong correlation between the behavior of power consumption and weather variables such as temperature, humidity, wind speed and cloud cover.

In general, except for Tuesday to Friday which are weekdays i.e. working days, the load profile of each other day of the week is distinct, which necessitate the use of single NN for the days of similar load profiles i.e. Tuesday to Friday and one NN for each day with distinct load profile [11]. Monday and Saturday are excluded from week days since Monday being startup day includes pickup loads and Saturday being adjacent to holiday i.e. Sunday have different load profile than weekdays. Weather status is classified and set to the corresponding measuring value for e.g. fine (1.0) and cloudy (0.9) etc. [18]. The inputs to the hybrid system may include temperature, rain indication, seasonal variation and historical load data [13].

The goal of the present work is to investigate the effect of wind direction and weather event for modeling the STLF problem. Future load forecasts are mainly affected by the assumption that the factors which determine the level and patterns of usage in the past will continue to hold good in the future also. So far to the best of our knowledge, work reported in different published literatures, authors do not consider the effect of wind direction on STLF. This motivates to develop a STLF model which would be sensitive to wind direction along with weather event and temperature. For this, the model so developed is season specific and region specific. This work does not study the forecasting for special days, such as religious and legal holidays. Special days have different consumption profiles from ordinary days, which make forecasting very difficult for them. The simulation work has carried on with the data of Tuesday through Friday in winter season comprising the months of December, January, February and first half of the month March and the region selected is Norwalk/Stamford of Connecticut State in United States of America. The versatility of this model is displayed through tests on actual load data of utility Connecticut Valley Electric Exchange and its corresponding weather data [29], [30].

Parameters affecting a day ahead average load are identified as historical load, temperature, weather event (for e.g. fog, snow etc.) and wind direction. Among these parameters, weather event and wind direction are linguistic qualitative terms and rest have numerical values. Weather event and wind direction affect the load demand and numeric value of their combined effect on load is determined using Fuzzy logic technique. This numeric value of ‘Effect on load’ is one of the inputs to NN architecture and the other input parameters of NN are historical load and temperature data. The output of the NN architecture will be the next day i.e. forecast day average load as shown in Figure 1.

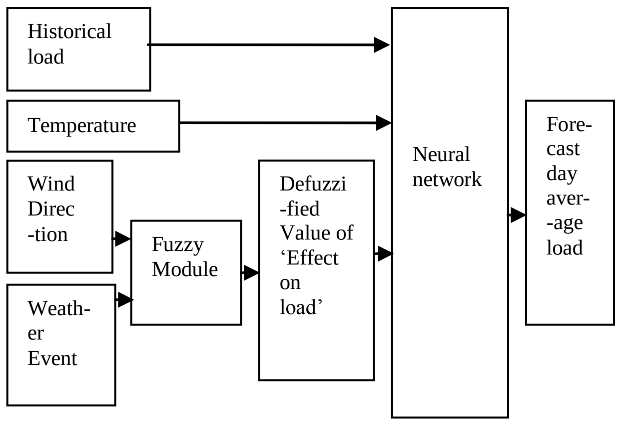


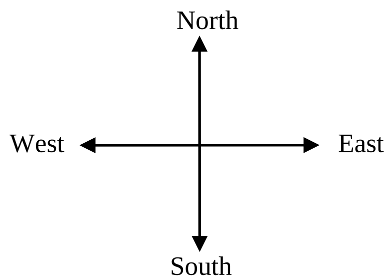
Figure 1. Basic Hybrid Neuro-Fuzzy Based STLF Model

2. Geography of the Region

For developing a STLF model which would be sensitive to wind direction and weather event, the region so selected is Norwalk and Stamford cities of Connecticut State in United States of America situated along the sea shore.

Physical location and geography of the region are given in Figure 2 and Figure 3 respectively. Both the cities have moderate mid latitude continental climate and distance between them is approximately 15 kilometer. Connecticut valley electric exchange supplies electricity to these cities and their combined electric load data are published in utility's website www.cvx.com [29]. Being close to each other, their climatic conditions are also the same and single weather report is published for both the cities [30].

Wind direction indirectly affects the electricity consumption. During winter, wind coming from the sea side has different effect on load than that coming from the inland. Wind blowing from the inland (for e.g. wind direction WSW i.e. from Appalachian mountain side) is colder than the wind coming from the sea side (for e.g. Wind direction South and SSW). When cold wind blows from inland it causes more discomfort to the people and electricity consumption is higher to meet out increase in heating requirement whereas when wind blows from seaside electricity consumption is lesser as these winds do not cause discomfort to the people. Therefore, during winter season, when wind blows from inland, electricity consumption is more in comparison to, when it blows from the seaside. For e.g., on dates 21.12.2006 and 04.01.2007 'mean temperature' and 'weather event' were same i.e. '6°centigrade' and 'scattered cloudy as weather event' respectively. However on 21.12.2006, wind direction was West north west (WNW) and on 04.01.2007, wind direction was South west (SW). The effect on load due to wind direction WNW is more pronounced than that of wind direction SW, as a result average load consumed was 579 MW on 21.12.2006 as compared to that of 542 MW on 04.01.2007.



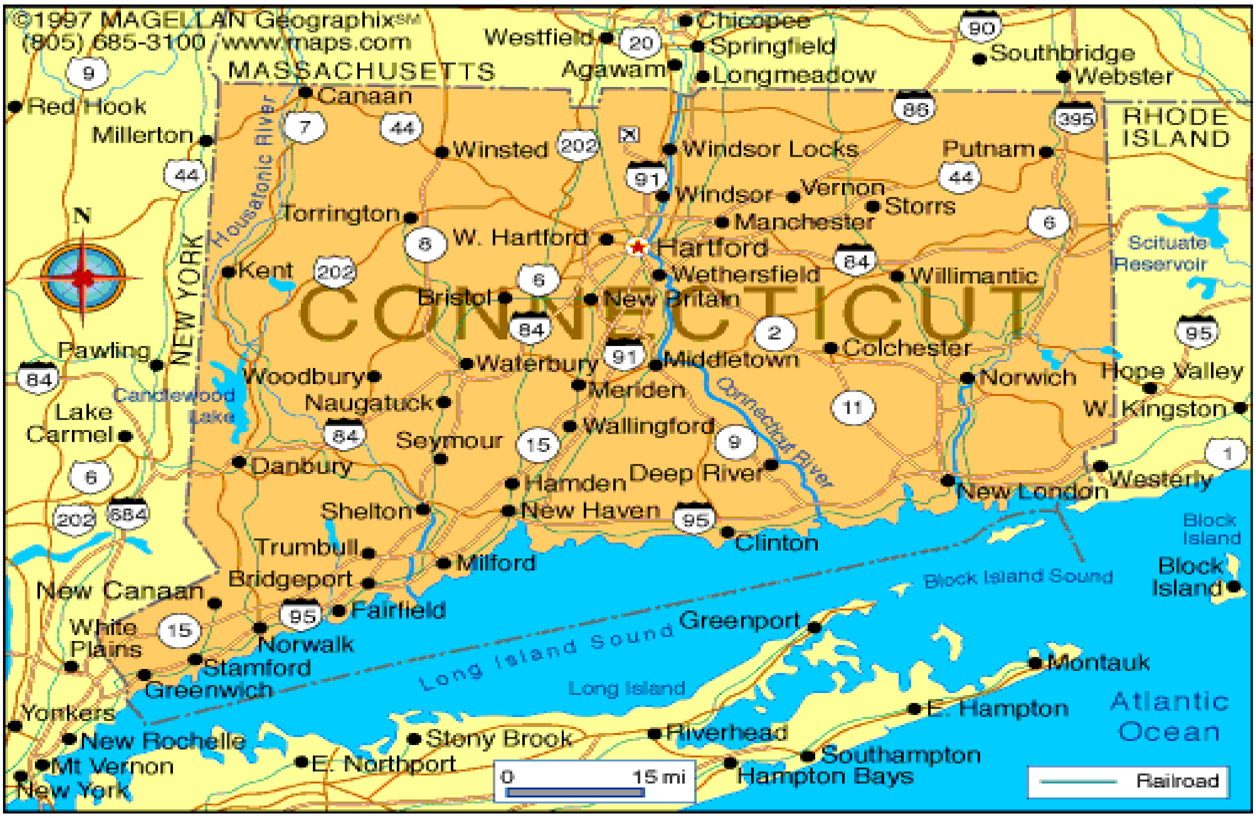


Figure 2. Physical Location of Norwalk/Stamford

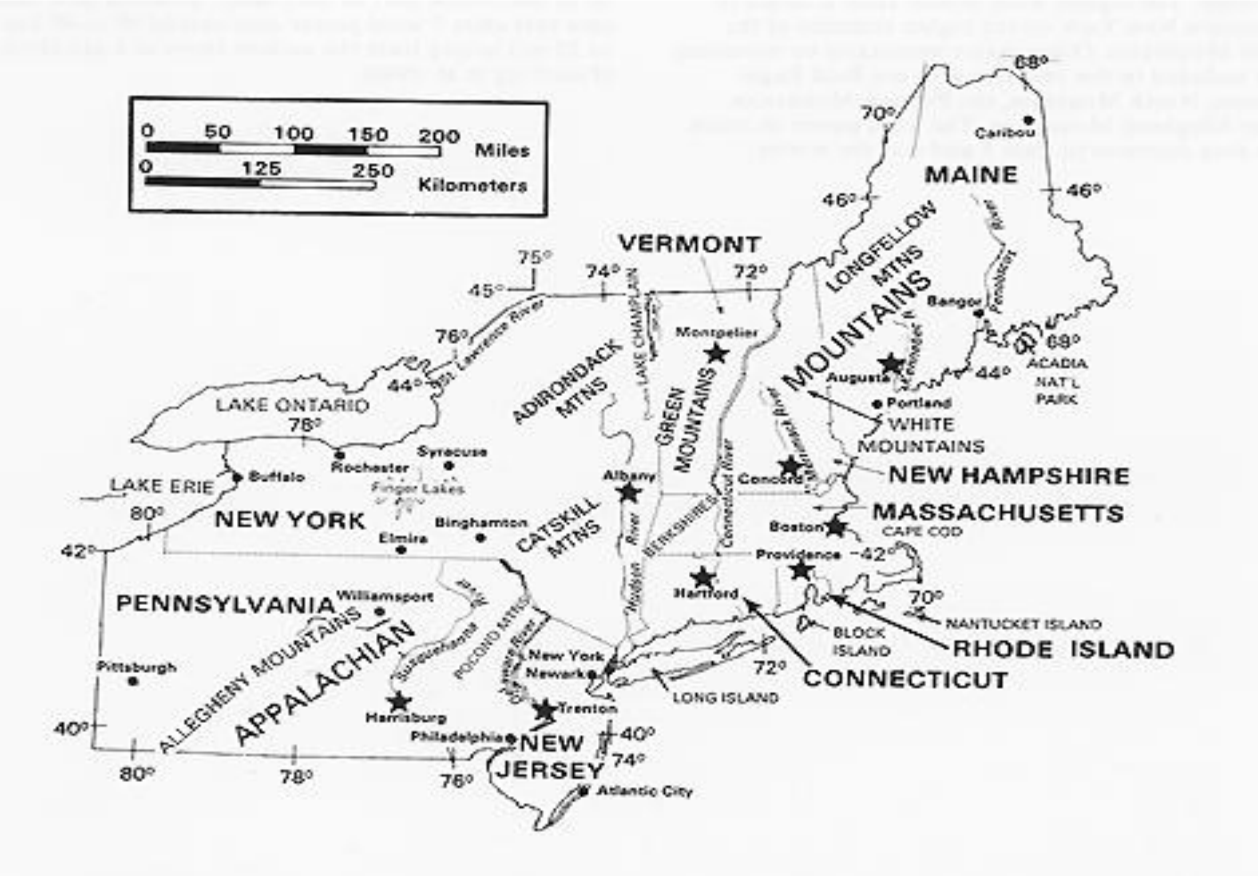


Figure 3. Geography of the Region

3. Fuzzy Implementation

The inputs to the fuzzy module in Figure 1 are weather event and wind direction which are two fuzzy sets [25, 2005, pp. 61-76].

3.1. Fuzzy Sets

3.1.1. Wind Direction

During winter season, wind blowing from the direction of inland is colder than the wind blowing from the direction of sea side. Therefore, when wind blows from inland electricity consumption is more in comparison to, when wind blows from the seaside to meet out more heating requirement. Wind directions are classified and assigned corresponding numerical value depending upon their effect on load, thus forming a universe of discourse: North north east (NNE) 1.0, North (N) 1.0, North north west (NNW) 1.0, North west (NW) 1.0, West north west (WNW) 1.0, West (W) 1.0, West south west (WSW) 1.0, East north east (ENE) 0.625, North east (NE) 0.5, South west (SW) 0.375, South south west (SSW) 0.25, South (S) 0.25, South south East (SSE) 0.25, East (E) 0.25 and East south east (ESE) 0.25. Wind directions have different effect on load and are assigned membership function accordingly. Wind directions for e.g. NNE, N, NW, W, and WSW have maximum effect on load and during winter cause increase in demand of load. These are assigned membership function ‘Strong’. Wind direction NE has medium effect on load and assigned membership function ‘Normal’. Wind directions like SSW, S, E and ESE have no significant effect on load and are assigned membership function ‘Light’.

3.1.2. Weather Event

Weather events are classified and assigned corresponding numerical values depending upon their effect on load, thus forming a universe of discourse: snow (1.0), overcast (0.6875), fog (0.6875), rain (0.5), mostly cloudy (0.5), cloudy (0.5), haze (0.375), scattered cloud (0.25), partly cloudy (0.25) and clear (0.25) [18]. Weather events have different effect on load and are assigned membership function accordingly. Weather event like ‘snow’ has maximum effect on load and during winter causes increase in demand of load. This is assigned membership function ‘Harsh’. Weather event like ‘rain’ has medium effect on load and assigned membership function ‘Moderate’. Weather event like ‘scattered cloud’ or ‘clear’ has no significant effect on load and are assigned membership function ‘Pleasant’.

3.2. Designing membership functions

Parameterizable membership functions: trapezoidal membership function and triangular membership function are used. Parameterized membership functions not only reduce the system design time, it also facilitate automated tuning of the system because desired changes to membership function (e.g. widening vs. narrowing a membership function) can be directly related to corresponding changes in the related parameters. Similar membership functions are used for two input conditions which are Wind Direction and Weather Event and single output of fuzzy module i.e. ‘Effect on load’ as shown in Figures 4-6.

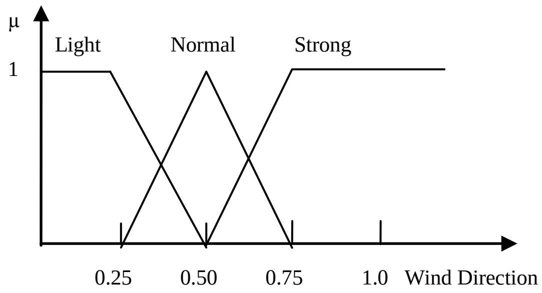


Figure 4. Membership Function of Wind Direction

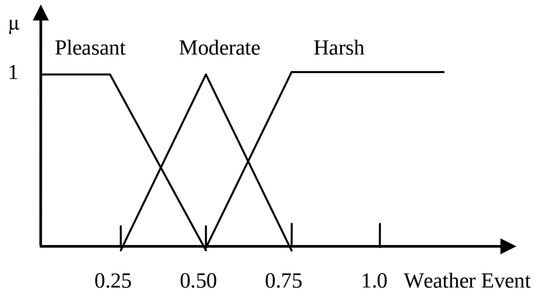


Figure 5. Membership Function of Weather Event

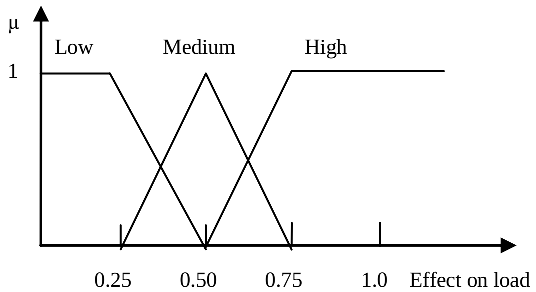


Figure 6. Membership Function of Effect on Load

3.3. Structure of Fuzzy Rules

To approximate an unknown system using fuzzy model it is desired that the model should include only important rules from the rule base which cover the input–output space of the system because generalizing ability of the model decreases as the number of rules increases [23]. Accordingly nine rules which are best describing the system are framed combining conditions on weather event and wind direction using conjunction (AND). The rules are:

Rule 1: IF Weather Event is *Pleasant* AND Wind Direction is *Light* THEN Effect on load is *Low*

Rule 2: IF Weather Event is *Pleasant* AND Wind Direction is *Normal* THEN Effect on load is *Low*

Rule 3: IF Weather Event is *Pleasant* AND Wind Direction is *Strong* THEN Effect on load is *Medium*

Rule 4: IF Weather Event is *Moderate* AND Wind Direction is *Light* THEN Effect on load is *Medium*

Rule 5: IF Weather Event is *Moderate* AND Wind Direction is *Normal* THEN Effect on load is *Medium*

Rule 6: IF Weather Event is *Moderate* AND Wind Direction is *Strong* THEN Effect on load is *High*

Rule 7: IF Weather Event is *Harsh* AND Wind Direction is *Light* THEN Effect on load is *High*

Rule 8: IF Weather Event is *Harsh* AND Wind Direction is *Normal* THEN Effect on load is *High*

Rule 9: IF Weather Event is *Harsh* AND Wind Direction is *Strong* THEN Effect on load is *High*

3.4. Fuzzy Rule Based Inference

The algorithm for fuzzy rule-based inference consists of following four basic steps.

3.4.1. Fuzzy Matching

The degree to which input data match the condition of fuzzy rule is calculated in Fuzzy matching process. ‘Min’ operator is used for combining the degree of matching of conjunction conditions for ‘Effect on load’ selection rules.

For e.g. Weather event ‘Fog’ in the universe of discourse ‘Weather Event’ is represented by the numerical value 0.6875 and Wind direction ‘North East’ in the universe of discourse ‘Wind Direction’ is represented by the numerical value 0.5. Weather event ‘Fog’ and wind direction ‘North East’ are represented by two rules. As per one rule weather event ‘Fog’ matches membership function ‘Moderate’ and wind direction ‘North East’ matches membership function ‘Normal’. Combining these two matching degrees using ‘min’ operator, let matching degree ‘x’ is obtained which corresponds to the input data matching the antecedent of the following first rule:

IF Weather Event is Moderate AND
Wind Direction is Normal
THEN Effect on load is Medium

As per other rule, weather event ‘Fog’ matches membership function ‘Harsh’ and wind direction ‘North East’ matches membership function ‘Normal’. Combining these two matching degrees using ‘min’ operator, let matching degree ‘y’ is obtained which corresponds to the input data matching the antecedent of the other rule given as:

IF Weather Event is Harsh AND
Wind Direction is Normal
THEN Effect on load is High

3.4.2. Inference

After the fuzzy matching step, a fuzzy inference step using clipping method is invoked for each of the two rules to produce a conclusion based on their matching degree.

3.4.3. Combining Fuzzy Conclusion

Inference results of both rules are combined by superimposing fuzzy conclusions of the rules applying max fuzzy disjunction operator.

3.4.4. Fuzzy Matching

In this work centroid defuzzification technique is used which calculates the weighted average of fuzzy set and for parameter ‘Effect on load’ the defuzzified value comes to 0.73 for the example discussed above. By this way, all possible defuzzified/numeric values of ‘Effect on load’ are obtained.

‘Effect on load’ is one of the input parameter for the NN and other input parameters of NN are historical load and temperature data. The output of this NN architecture will be the forecast day average load.

4. Neural Network Application

4.1. Selection of Training Cases

Present work concentrates on developing the forecast model for winter season only. Daily electricity load and weather data for winter season and working day i.e. Tuesday to Friday in respect of Norwalk/Stamford in Connecticut State of United States of America have been considered in this work [29], [30]. Since only load is forecasted for next day i.e. forecast day, other inputs if required in respect of forecast day for any input structures, are acquired as it is from the weather report [30]. Winter season comprises the months of December, January, February and first half of the March. The data sets are taken for full winter season in the year 2005, 2006, 2007 and for the year 2008 data comprise the months of January, February and first half of the March only. Average load data for a day is obtained by averaging the hourly load data for 24 hours in a day [29]. Few load data are missing and are filled in by interpolating between neighboring values. Total, one hundred and three maximum possible data sets are taken over the year 2005, 2006, 2007 and 2008. Among these seventy three data sets are used for training, sixteen for validation and fourteen for testing the model. Training, validation and test data are spread over the year 2005, 2006, 2007 and 2008. Training cases include data from previous years to follow the changes in yearly load pattern [10]. Therefore, all load and weather conditions are represented in the training, validation and test data in order that the model adapt to all conditions.

4.2. Network Structure

ANN structure used is a three layered feed-forward neural network trained by the back propagation algorithm based on Levenberg-Marquardt approach [24]. This ANN structure comprises an input, a hidden, and an output layer. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The processing units of the hidden and output layers have a non-linear hyperbolic tangent transfer function and identity transfer function respectively. Each layer is connected to the layer above it in a feed forward manner. For normalizing the input data in required range [−1, 1], following formula is used:

$$L_N = 2 \times \frac{L - \min(L)}{\max(L) - \min(L)} - 1 \qquad (1)$$

where, L_N is the normalized value, L the actual value, min (L) the minimum value and max (L) the maximum value.

The approach is static in the sense that the problem of load forecasting is approached by making forecast for one whole day at a time. A single Multi Layer Perceptron (MLP) network is used for days Tuesday to Friday. Network has one hidden layer between input and output layers. Single output node is considered, representing forecast day average load. Another features decided about the architecture of the network are the input variables and the number of hidden layer neurons.

For the input variables, following symbols are used:

La(i – 1) = a day ahead average load
Ly(i – 365) = average load of the day, which is a year ahead of forecast day
Ta(i – 1) = a day ahead mean temperature in °centigrade
Ty(i – 365) = mean temperature in °centigrade, of the day which is a year ahead of forecast day
Tf(i) = forecast day mean temperature in °centigrade
Ea(i – 1) = a day ahead defuzzified value of 'Effect on load'
Ey(i – 365) = defuzzified value of 'Effect on load' of the day, which is a year ahead of the forecast day
Ef(i) = forecast day defuzzified value of 'Effect on load'

index *'i'* represents the forecast day, *'i – 1'* represents a day ahead of forecast day and '*i* – 365' represents a day which is a year ahead of the forecast day.

Output variable: *Lf(i)* is forecast day average load

Four different input structures are tested separately. These are numbered as 1 to 4.

Input structures are:
1. *La(i – 1), Ta(i – 1), Ly(i – 365), Ty(i – 365), Tf (i), Ea (i – 1), Ey(i – 365), Ef (i)*
2. *La(i – 1), Ta(i – 1), Ly(i – 365), Ty(i – 365), Tf (i)*
3. *La(i – 1), Ta(i – 1), Ly(i – 365), Ty(i – 365), Tf (i), Ea (i – 1), Ef (i)*
4. *La(i – 1), Ta(i – 1), Ly(i – 365), Ty(i – 365), Tf (i), Ea (i – 1), Ey(i – 365)*

Processing with this ANN structure is carried out in two phases. During first phase, ANN model is trained with training data to obtain nonlinear input output mapping. The mapped network in the form of free parameters (weights) is stored in the ANN structure in a distributed manner. These weights give a functional relationship between input and output of training data. Performance goal of the ANN structure is set at 0.1 MW and learning rate as 0.1. After the network is properly trained i.e. performance goal is met, network response is tested with new input data not seen before by the network.

The implementation of NN model is carried out using MATLAB Neural Network Toolbox [28].

5. Results and Discussion

Average percentage forecasting error is used as a measure of performance for all the four input structures. Average percentage forecasting error E_{av} is defined as:

$$E_{av} = \frac{1}{N}\sum_{i=1}^{N}\left[\left|\frac{Y_a(i) - Y_f(i)}{Y_a(i)}\right|\right] \times 100 \qquad (2)$$

where,
N is the number of test data cases
$Y_a(i) = i$ *th* actual load value
$Y_f(i) = i$ *th* load forecast value i.e output of ANN structure

While keeping same neural network architecture for all the four input structure, the next day average load forecast is obtained for the fourteen test data as shown in Tables 1 to 4.

Table 1. Input structure 1

1. *La(i – 1), Ta(i – 1), Ly(i – 365), Ty(i – 365), Tf (i), Ea (i – 1), Ey(i – 365), Ef (i)*

	Actual load in MW	Load forecast value in MW	Error in MW	% Absolute Error	E_{av}
Data 1	632	627.8737	4.1263	0.6529	1.778
Data 2	645	651.2437	-6.2437	0.968	
Data 3	680	672.6365	7.3635	1.0829	
Data 4	643	649.2098	-6.2098	0.9658	
Data 5	646	640.9736	5.0264	0.7781	
Data 6	600	593.2409	6.7591	1.1265	
Data 7	609	602.4771	6.5229	1.0711	
Data 8	619	623.0671	-4.0671	0.657	
Data 9	679	642.537	36.463	5.3701	
Data 10	640	638.0645	1.9355	0.3024	
Data 11	544	583.2242	-39.224	7.2103	
Data 12	586	588.4097	-2.4097	0.4112	
Data 13	651	659.7831	-8.7831	1.3492	
Data 14	604	621.7954	-17.795	2.9463	

Table 2. Input structure 2

2. *La(i – 1), Ta(i – 1), Ly(i – 365), Ty(i – 365), Tf (i)*

	Actual load in MW	Load forecast value in MW	Error in MW	% Absolute Error	E_{av}
Data 1	632	632.2208	-0.2208	0.0349	2.545
Data 2	645	661.4498	-16.45	2.5504	
Data 3	680	670.3441	9.6559	1.42	
Data 4	643	663.4299	-20.43	3.1773	
Data 5	646	639.9741	6.0259	0.9328	
Data 6	600	601.4772	-1.4772	0.2462	
Data 7	609	587.5956	21.4044	3.5147	
Data 8	619	611.2295	7.7705	1.2553	
Data 9	679	666.8672	12.1328	1.7869	
Data 10	640	640.6751	-0.6751	0.1055	
Data 11	544	600.4026	-56.403	10.368	
Data 12	586	617.7329	-31.733	5.4152	
Data 13	651	639.4507	11.5493	1.7741	
Data 14	604	622.4277	-18.428	3.051	

Table 3. Input structure 3

3. *La(i – 1), Ta(i – 1), Ly(i – 365), Ty(i – 365), Tf (i), Ea (i – 1), Ef (i)*

	Actual load in MW	Load forecast value in MW	Error in MW	% Absolute Error	E_{av}
Data 1	632	625.2198	6.7802	1.0728	1.997
Data 2	645	647.2165	-2.2165	0.3436	
Data 3	680	668.306	11.694	1.7197	

Data 4	643	669.1331	-26.133	4.0642	
Data 5	646	633.7509	12.2491	1.8961	
Data 6	600	604.7413	-4.7413	0.7902	
Data 7	609	586.2987	22.7013	3.7276	
Data 8	619	617.6659	1.3341	0.2155	
Data 9	679	671.1541	7.8459	1.1555	
Data 10	640	638.1794	1.8206	0.2845	
Data 11	544	576.5845	-32.585	5.9898	
Data 12	586	599.464	-13.464	2.2976	
Data 13	651	648.3286	2.6714	0.4103	
Data 14	604	628.1034	-24.103	3.9906	

Table 4. Input structure 4

4. *La(i – 1), Ta(i – 1), Ly(i – 365), Ty(i – 365), Tf (i), Ea (i – 1), Ey(i – 365)*

	Actual load in MW	Load forecast value in MW	Error in MW	% Absolute Error	E_{av}
Data 1	632	623.429	8.571	1.3562	1.735
Data 2	645	654.56	-9.56	1.4822	
Data 3	680	678.5405	1.4595	0.2146	
Data 4	643	646.1098	-3.1098	0.4836	
Data 5	646	641.1293	4.8707	0.754	
Data 6	600	596.1394	3.8606	0.6434	
Data 7	609	607.9175	1.0825	0.1778	
Data 8	619	624.9135	-5.9135	0.9553	
Data 9	679	642.5366	36.4634	5.3702	
Data 10	640	634.1377	5.8623	0.916	
Data 11	544	584.4007	-40.401	7.4266	
Data 12	586	590.849	-4.849	0.8275	
Data 13	651	660.6907	-9.6907	1.4886	
Data 14	604	617.2132	-13.213	2.1876	

In first case of input structure 1, parameter ‘Effect on load’ for a day ahead, a year ahead and forecast day, along with other five parameters involving temperature and historical load data are selected as input parameters. Simulation results show that the forecast error for this case is 1.778 %.

In second case of input structure 2, only five parameters consisting temperature and historical load data are selected as influential input parameters. No fuzzy logic technique is used and load forecast model consists of only NN structure. The forecast error is 2.545 %.

In third case of input structure 3, parameter ‘Effect on load’ for a day ahead and forecast day, along with other five parameters involving temperature and historical load data are selected as influential input parameters. The forecast error is 1.997 %.

Finally in fourth case of input structure 4, parameter ‘Effect on load’ for a day ahead and a year ahead, along with other five parameters involving temperature and historical load data are selected as input parameters. The forecast error for this structure is 1.735 % as shown in Figure 7.

The comparison of all four simulation results revealed that the performance of the input structure 4 is the best as it gives the least error. Average percentage forecasting error is 1.735 % for input structure 4. It also proves that weather event and wind direction are other important factors affecting the load forecast and can be used as input parameters in an efficient load forecast model. Further, the performance of hybrid neuro-fuzzy model of fourth structure is better than the simple neural network based model of second structure which confirms the superiority of neuro-fuzzy approach over simple neural network based approach.

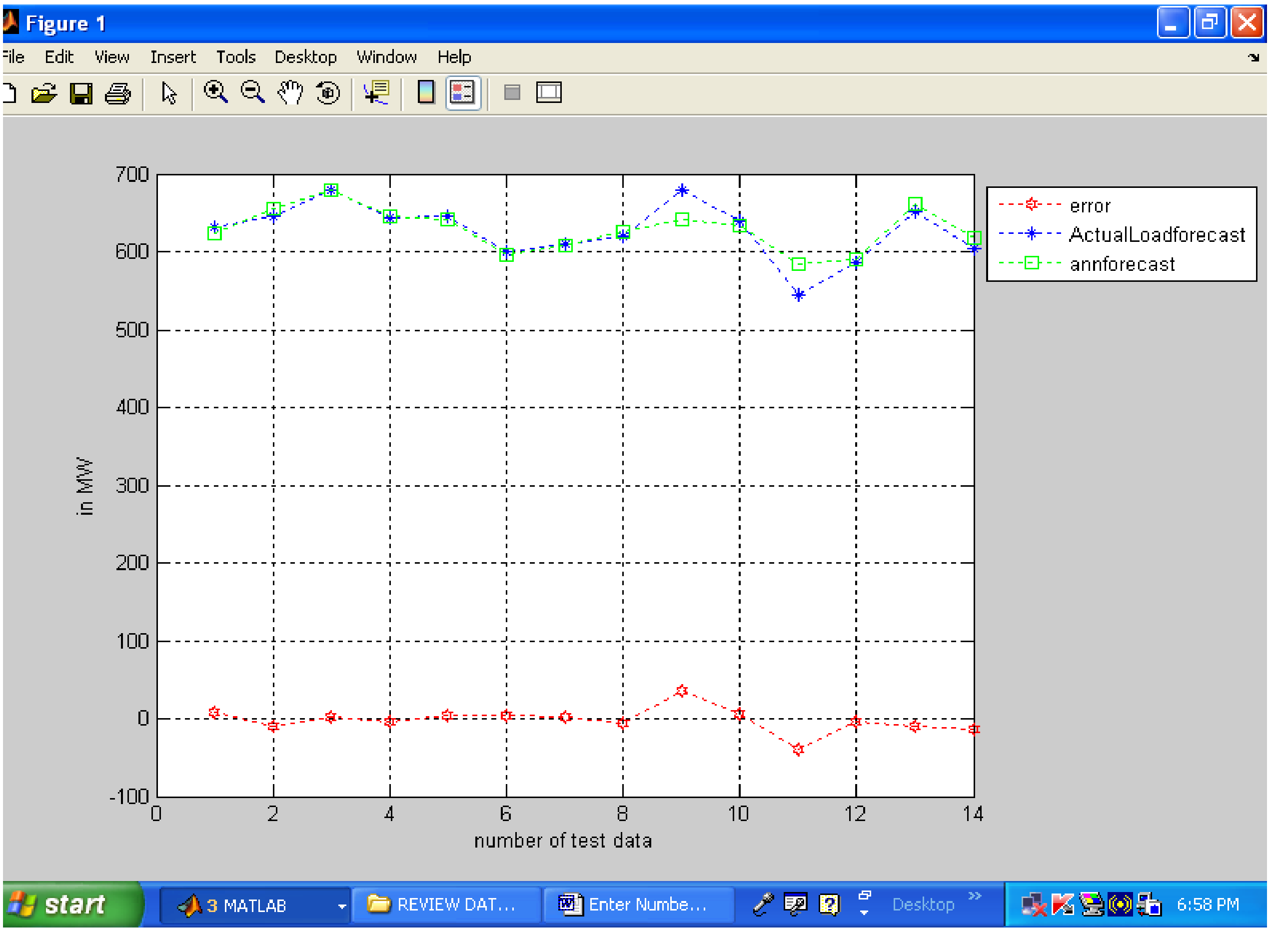


Figure 7. Test Result for Input Structure 4

6. Conclusions

This paper studied the effect of wind direction and weather event for modeling the STLF problem and following conclusions are drawn.

- Although cooling power is captured in parameter 'temperature' however when 'temperature' alone is used along with 'historical load data' in Input structure 2, results are not encouraging and the forecast error is 2.545 %. This forecast error is significantly reduced to 1.735 % for Input structure 4, when inputs involving parameters 'wind direction' and 'weather event' are selected along with parameters involving 'temperature' and 'historical load data'. This concludes that 'wind direction' and 'weather event' are important factors other than 'temperature' and 'historical load data' affecting the STLF.
- The hybrid neuro fuzzy based model which uses all possible input parameters including wind direction and weather event is simple and efficient in simulation of nonlinear load forecasting problem.
- The Input structure 4, giving least error of 1.735% utilized the data for weather information and wind direction of a year before and thus adapt to the changes in yearly load pattern.
- The current implementation and the rules are specific for region Norwalk/Stamford in Connecticut State of United States of America but can be utilized in any other area where the wind direction considerably affects the load forecast.
- The fuzzy knowledge base can be expanded to include additional rules for other season since the seasonal effect changes the load pattern considerably. However the same neural network can be used for other models also.
- Proposed model is selected according to the characteristics of the system, because the sensitivities of the input variables are varied as the system condition changes. For instance the wind direction is an important parameter for load forecasting in temperate zone of Norwalk/Stamford, however, in tropical area and in summer season for e.g. in India load may not be sensitive to the wind direction and humidity will be an important parameter for the load forecasting.
- This paper forecast next day average load. Next day total load requirement can easily be calculated by multiplying 24 to the value of next day average load where 24 stands for total numbers of hours in a day.
- Finally, so far to the best of our knowledge the effect of wind direction is considered for the first time in developing the load forecast model.

In conclusion, it is our hope that the inclusion of wind direction as one of the input parameters for load forecasting has opened a new and interesting dimension in the discipline of load forecasting.

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Ashish Kumar Srivastava received his B.Tech degree in Electrical Engineering from Institute of Engineering and Technology, Lucknow, (Lucknow University), India in 1991 and M.Tech degree in 'Electrical Power System Management' from Jamia Millia Islamia (Central University), New Delhi, India in 2008.

His fields of interest include power system operation and application of artificial intelligence techniques in power system.

Tariqul Islam received his MSc Engineering degree in Instrumentation and Control Systems from Aligarh Muslim University, India in 1997 and PhD from the IC Design and Fabrication Center, Department of Electronics and Telecommunication Engineering, Jadavpur University, Kolkata, India.

Presently he is working as Associate Professor in Electrical Engineering Department, Jamia Millia Islamia (Central University), New Delhi, India. His current research interests are development of sensors, sensor array, smart sensors and applications of neural networks and fuzzy logic for processing of sensor signals.