# Short Term Load Forecasting Using Adaptive Neuro - Fuzzy Inference System

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*Abstract-* **In today world, load forecasting is very important for the power system operation. The meaning of Load forecasting is to predicting the future load with the help of historical load data available. For the Power system management scheduling and dispatching operations load forecasting plays an important role and it also concerns the prediction of energy demand in different time spans. Data for the present work includes the Load data and the weather data that affects the load forecasting. These data are obtained from reliable and genuine source such as the Madhya Pradesh Purva Kshetra Vidyut Vitran Company Ltd. (MPPKVVCL) Jabalpur of the winter season i.e. from recent month January 2018(every 15min) and weather data from www.worldweatheronline.com. From the analysis carried out on the ANFIS based Model mean absolute percentage error for a typical Wednesday was found to be 2.23%**

**Index Terms- Short Term Load forecasting, ANFIS.**

## INTRODUCTION

Load forecasting helps an electric usefulness to make important selection including selections on purchasing and generating electric load, load switching, and infrastructure development. The meaning of Load forecasting is to forecast the future demand with the help of historical load data available. Load forecasts are highly important for energy suppliers and other participator in electric energy generation, transmission, distribution and market. The accurate forecasting of the load is an essential element in power system.

Load Forecast are used to decide whether extra generation must be provided by increasing the output of online generators, by committing one or more extra units, or by the exchange of power with neighbouring systems. Load forecasts are also used to decide whether the output of an already running generation unit should be decreased or switched off, which is find out by functions called generation control functions, such as scheduling, coordination, unit-commitment and interchange evaluation.[1]

For good service of electricity, the customers require a safe and uninterrupted power supply. A poor service of load forecast misleads planners and often results in wrong and sometime expensive expansion plans. If any negative error in the forecast result could affect consumer's production levels, especially for larger power users. Accurate forecasts are required for power system security and its overall reliability.[2]

## ABOUT ANFIS

Adaptive network based fuzzy inference system (ANFIS) is a neuro fuzzy technique where the fusion is made between the neural network and the fuzzy inference system. The neural network has the inherent advantage of being able to adapt itself and also in its learning capabilities. The striking component that is related with the fuzzy rationale is the particular capacity to consider the common vulnerability and imprecision of genuine frameworks with the assistance of the fuzzy if-then guidelines.[5]

Structure of the Sugeno model is designed in such a way that the input is mapped to input membership function, the input membership function is mapped to rule, then the rule is mapped to output membership function and then the output membership function is mapped to the output. The system takes five layers. The first layer of each node generates a membership grade. Each node in the second layer calculates the firing strength of the rule. Each node in the third layer calculates the ratio of the $i^{th}$ rule's firing strength to the total of all firing strength. Each node in the fourth layer is an adaptive node which maps to the output membership functions. The node in the fifth layer gives the overall output.

For a first-order Sugeno fuzzy model, a typical rule set with two fuzzy if-then rules can be expressed as:

Rule: 1 If $x_1$ is $A_1$ and $x_2$ is $B_1$,
Then $y_1 = p_1 x_1 + q_1 x_2 + r_1$,

Rule: 2 If $x_1$ is $A_2$ and $x_2$ is $B_2$,
Then $y2 = p_2 x_1 + q_2 x_2 + r_2$,

Where [$A_1$, $A_2$, $B_1$, $B_2$] are called the premise parameters. [$p_i$, $q_i$, $r_i$] are called the consequent parameters, i = 1,2... The consequent parameters (p, q, and r) of the $n^{th}$ rule contribute through a first order polynomial of the form:

$$Y_n = p_n x_1 + q_n x_2 + r_n \qquad (1)$$

Where xn are the inputs, $Y_n$ are the outputs within the fuzzy region specified by the fuzzy rule, $p_n$, $q_n$, and $r_n$ are the design parameters that are determined during the learning process.

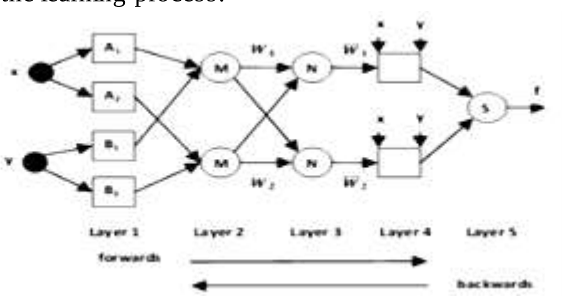


*Fig.1 ANFIS architecture for a two-input, two-rule first-order Sugeno model*

Specifically, ANFIS only supports Sugeno -type systems, and have the following properties:

1. Be first or Zeroth order Sugeno-type systems.
2. Have a single output, obtained using weighted average defuzzifcation. All yield enrollment capacities must be a similar sort and either be linear or constant.
3. Have no manage sharing. Different rules can't have a similar yield enrollment work, to be specific the quantity of yield participation capacities must be equivalent to the quantity of principles.
4. Have solidarity weight for each run the show.
5. The ANFIS engineering comprises of five layers with the yield of the nodes in each separate layer spoke to by [4]

$O_1{}^{i}$, where i is the ith node of layer l.

The layer by layer description of a two input two rule first-orders Sugeno system is following:

Layer 1 Generate the membership grades: Each node in this layer is an adaptive node. The yields of this layer are the fuzzy enrollment review of the sources of info,

which are given by

$$O^{i}{}_{1} = \mu A_i (x) \qquad (2)$$

Where $O_1{}^{i}$, is participation capacity of $\mu$ Ai (x) and An is the linguistic name related with this node. In this layer parameter of every MF are balanced.

Layer 2 Generate the firing strengths. The nodes are fixed nodes denoted as $\pi$, indicating that they perform as a simple multiplier. Each node in this layer;2 calculates the firing strengths of each rule via multiplying the incoming signals and sends the product out. The outputs of this layer can be represented as

$O^{i}{}_{2} = w_i$ = m j=1

$\mu A_i (x)$ (3)

Layer 3 Normalize the firing strengths. The nodes are also fixed nodes. They are labeled with N, indicating that they play a normalization role to the firing strengths from the previous layer. The $i^{th}$ node of this layer calculates the ratio of the $i^{th}$ rule's firing strength to the sum of all rules firing strengths:

$$O^{i}{}_{3} = \bar{W}_i = w_i / w_1 + w_2 \qquad \cdot(4)$$

Layer 4 Calculate rule outputs based on the consequent parameters. Each node in this layer is adaptive node and in this layer parameters of output are adjusted. This output usually is a linear function of inputThe yield of every node in this layer is just the result of the standardized firing quality and a first-arrange polynomial. Hence, the yields of this layer are given by$O^{i}{}_{4} = y_i = \bar{W}_i \; f_i = \bar{W}_i \; (p_i \; x_1 + q_i \; x_2 + r_i)$ i = 1,2,3,4. .... (5)

Layer 5 Sum all the inputs from layer 4. There is only single fixed node labeled with$\sum$. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by

$$O^{i}{}_{5} = \sum Y_i = \sum \bar{W}_i \; f_i = (\bar{w}_1 \; x_1) \; p_1 + (\bar{w}_1 \; x_2) \; q_1 + \bar{w}_1 r_1 + (\bar{w}_2 \; x_2) \; p_2 + (\bar{w}_2 \; x_2) \; q_2 + \bar{w}_2 r_2 \ldots\ldots \qquad (6)$$

It is in this last layer that the consequent parameters can be solved for using a least square algorithm. Let us rearrange this last equation into a more usable form:

$$Y = [w_1 x_1 \quad w_1 x_2 \quad w_1 \quad w_2 x_1 \quad w_2 x_2 \quad w_2] \begin{bmatrix} p1 \\ q1 \\ r1 \\ p2 \\ q2 \\ r2 \end{bmatrix}$$

$= XW$ ..... (7)

When input-output training patterns exist, the weight vector (W), which consists of the consequent parameters, can be solved using a regression technique.

Good features of the ANFIS –

The advantages of ANFIS are compared to other artificial intelligent techniques such as an artificial neural network and an expert system.[4] The advantages are as follows:

- ANFIS gives a high precision in classification and prediction models.
- ANFIS has adaptive features to solve wrong data problem that involves new power network configuration. The situation is fairly hard to illuminate utilizing master system because of settled standards.
- ANFIS has an effective learning process on the training data while considering optimization in its implementation.

## RESULT

Training data set is considered from first three week of January (01/01/2018 – 21/01/2018) and Tested on Wednesday, 24/01/2018. In this case take a three input (Hours of the day, Week of the day and Temperature) and membership function is 6 for first input hours of the day (like early morning, morning, afternoon, evening, night and late night), membership function is 7 for second input day type (like Monday, Tuesday, Wednesday, Thursday, Friday, Saturday and Sunday) and membership function is 3 for last input winter temperature (like very low, low and medium) and process is completed in 150 epochs. A Mean absolute percentage error is 2.23%.

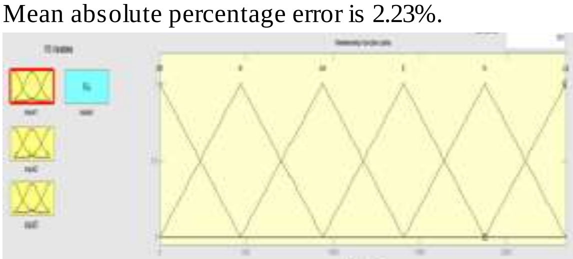

Fig- 2 Membership Function of 'Time'

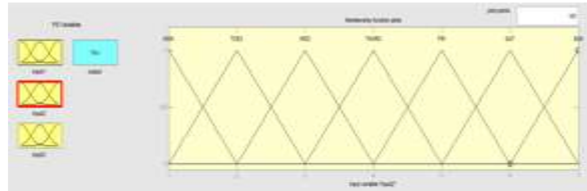

Fig- 3Membership Function of 'Week of the Day'

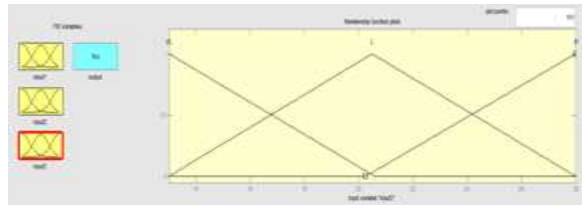

Fig- 4 Membership Function of 'Temperature'

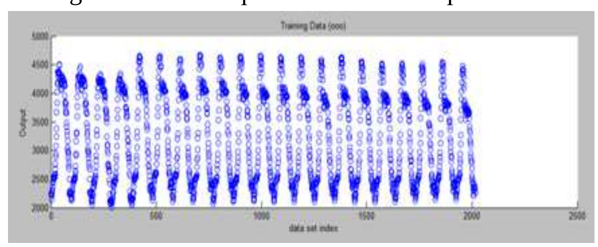

Fig 5 Training Data

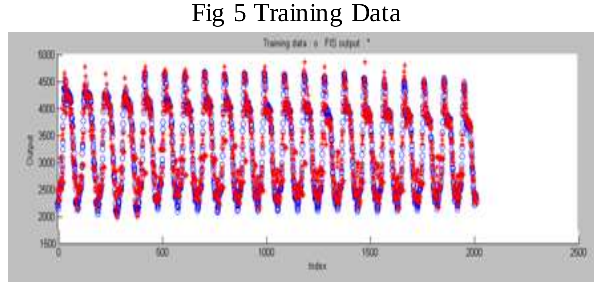

Fig 6 *Training data vs FIS output*

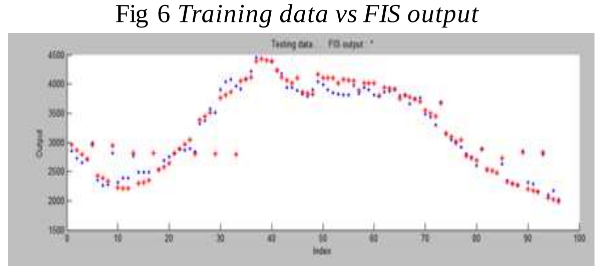

Fig 7 *Forecast output*

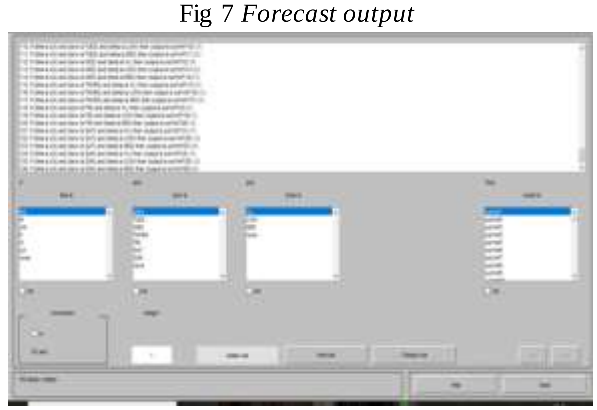

Fig.- 8 *Rules*

Fig. 9 Ruleviewer

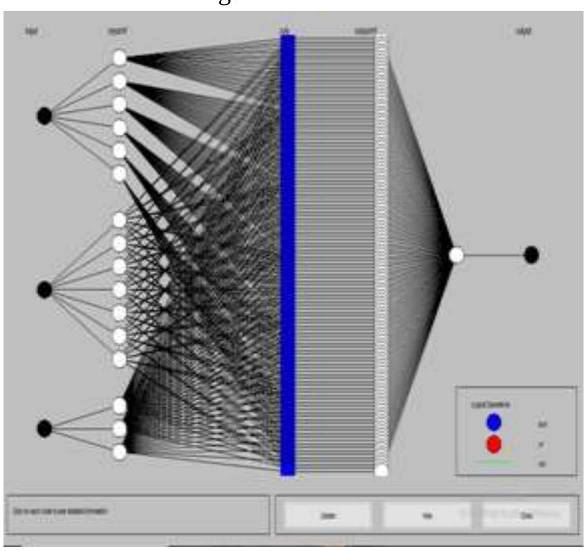

Fig. 10 Structure

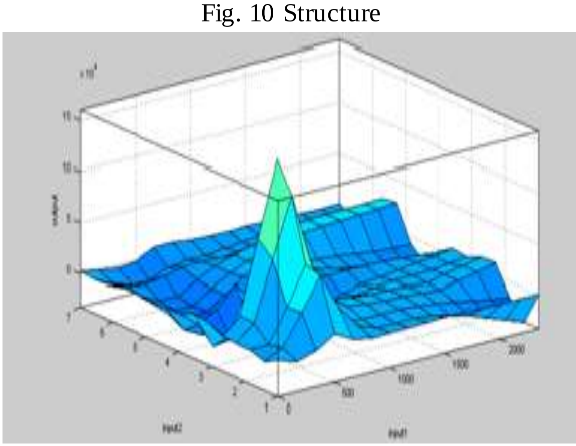

Fig 11Surface

RESULT

TABLE-1: ACTUAL DEMAND VS FORECAST DEMAND

| TIME | DAY OF THE WEEK | TEMPERATURE | ACTUAL DEMAND | FORECAST DEMAND |
|---|---|---|---|---|
| 0:00 | 3 | 18 | 2857 | 2960 |
| 00:15 | 3 | 18 | 2730 | 2870 |
| 00:30 | 3 | 18 | 2649 | 2790 |
| 00:45 | 3 | 18 | 2710 | 2710 |
| 00:1 | 3 | 18 | 2998 | 2950 |
| 1:15 | 3 | 18 | 2346 | 2430 |
| 1:30 | 3 | 18 | 2261 | 2380 |
| 1:45 | 3 | 18 | 2280 | 2340 |
| 2:00 | 3 | 18 | 2823 | 2940 |
| 2:15 | 3 | 18 | 2311 | 2220 |
| 2:30 | 3 | 18 | 2290 | 2210 |
| 2:45 | 3 | 18 | 2292 | 2210 |
| 3:00 | 3 | 17 | 2763 | 2820 |
| 3:15 | 3 | 17 | 2408 | 2300 |
| 3:30 | 3 | 17 | 2487 | 2320 |
| 3:45 | 3 | 17 | 2411 | 2350 |
| 4:00 | 3 | 17 | 2819 | 2820 |
| 4:15 | 3 | 17 | 2534 | 2530 |
| 4:30 | 3 | 17 | 2647 | 2580 |
| 4:45 | 3 | 17 | 2751 | 2640 |
| 5:00 | 3 | 17 | 2802 | 2810 |
| 5:15 | 3 | 17 | 2882 | 2890 |
| 5:30 | 3 | 17 | 2873 | 2930 |
| 5:45 | 3 | 17 | 2990 | 3005 |
| 6:00 | 3 | 17 | 2837 | 2810 |
| 6:15 | 3 | 17 | 3323 | 3340 |
| 6:30 | 3 | 17 | 3376 | 3450 |
| 6:45 | 3 | 17 | 3571 | 3510 |
| 7:00 | 3 | 17 | 3510 | 2985 |
| 7:15 | 3 | 17 | 3898 | 3770 |
| 7:30 | 3 | 17 | 4046 | 3920 |
| 7:45 | 3 | 17 | 4082 | 3960 |
| 8:00 | 3 | 17 | 3760 | **2994** |
| 8:15 | 3 | 17 | 3962 | 4005 |
| 8:30 | 3 | 17 | 4093 | 4080 |
| 8:45 | 3 | 17 | 4213 | 4110 |
| 9:00 | 3 | 20 | 4458 | 4390 |
| 9:15 | 3 | 20 | 4433 | 4440 |
| 9:30 | 3 | 20 | 4409 | 4400 |
| 9:45 | 3 | 20 | 4376 | 4390 |
| 10:00 | 3 | 20 | 4213 | 4250 |
| 10:15 | 3 | 20 | 4181 | 4110 |
| 10:30 | 3 | 20 | 3941 | 4040 |
| 10:45 | 3 | 20 | 3933 | 4002 |
| 11:00 | 3 | 20 | 3991 | 4010 |
| 11:15 | 3 | 20 | 3820 | 3860 |
| 11:30 | 3 | 20 | 3785 | 3840 |
| 1145 | 3 | 20 | 3848 | 3820 |
| 12:00 | 3 | 24 | 4046 | 4107 |
| 12:15 | 3 | 24 | 3988 | 4100 |
| 12:30 | 3 | 24 | 3998 | 4110 |
| 12:45 | 3 | 24 | 3953 | 4010 |
| 13:00 | 3 | 24 | 3894 | 4002 |
| 13:15 | 3 | 24 | 3897 | 4008 |
| 13:30 | 3 | 24 | 3889 | 4070 |
| 13:45 | 3 | 24 | 3977 | 4060 |
| 14:00 | 3 | 24 | 3841 | 3869 |
| 14:15 | 3 | 24 | 3940 | 4010 |
| 14:30 | 3 | 24 | 3899 | 4002 |
| 14:45 | 3 | 24 | 3888 | 4020 |
| 15:00 | 3 | 25 | 3790 | 3800 |
| 15:15 | 3 | 25 | 3863 | 3940 |
| 15:30 | 3 | 25 | 3870 | 3930 |
| 15:45 | 3 | 25 | 3897 | 3910 |

| TIME | DAY OF THE WEEK | TEMPERATURE | ACTUAL DEMAND | FORECAST DEMAND |
|---|---|---|---|---|
| 16:00 | 3 | 25 | 3801 | 3750 |
| 16:15 | 3 | 25 | 3802 | 3810 |
| 16:30 | 3 | 25 | 3661 | 3780 |
| 16:45 | 3 | 25 | 3746 | 3740 |
| 17:00 | 3 | 25 | 3788 | 3730 |
| 17:15 | 3 | 25 | 3491 | 3505 |
| 17:30 | 3 | 25 | 3438 | 3500 |
| 17:45 | 3 | 25 | 3301 | 3400 |
| 18:00 | 3 | 25 | 3483 | 3480 |
| 18:15 | 3 | 25 | 3134 | 3150 |
| 18:30 | 3 | 25 | 3048 | 3070 |
| 18:45 | 3 | 25 | 2975 | 3020 |
| 19:00 | 3 | 22 | 2914 | 3040 |
| 19:15 | 3 | 22 | 2802 | 2780 |
| 19:30 | 3 | 22 | 2756 | 2745 |
| 19:45 | 3 | 22 | 2805 | 2700 |
| 20:00 | 3 | 22 | 2899 | 2880 |
| 20:15 | 3 | 22 | 2513 | 2550 |
| 20:30 | 3 | 22 | 2515 | 2510 |
| 20:45 | 3 | 22 | 2481 | 2485 |
| 21:00 | 3 | 22 | 2629 | 2703 |
| 21:15 | 3 | 22 | 2351 | 2330 |
| 21:30 | 3 | 22 | 2300 | 2290 |
| 21:45 | 3 | 22 | 2274 | 2280 |
| 22:00 | 3 | 18 | 2852 | 2830 |
| 22:15 | 3 | 18 | 2311 | 2290 |
| 22:30 | 3 | 18 | 2285 | 2170 |
| 22:45 | 3 | 18 | 2160 | 2140 |
| 23:00 | 3 | 18 | 2790 | 2803 |
| 23:15 | 3 | 18 | 2103 | 2040 |
| 23:30 | 3 | 18 | 2177 | 2080 |

## CONCLUSION

The main objective of this work is to provide power system planners with an accurate and reliable short-term load forecasting (STLF) system which may assist to economically optimize power system operations. The data for thesis obtained from reliable and genuine source such as the official website of Madhya Pradesh Purva Kshetra Vidyut Vitran Company Ltd. (MPPKVVCL), Madhya Pradesh, India and weather department Jabalpur, Madhya Pradesh , India in addition to some weather forecasting websites. The general goal of this investigation is to give control system dispatchers a precise and advantageous short-term load forecasting (STLF) system, which expands the power system unwavering quality and decrease the system task cost. In the advanced power showcase, the energy exchange and the spot value foundation depend on an exact load forecasting result.

## FUTURE WORK

This thesis can be extended in by the inclusion of these following recommendations: More parameter can be included in the present study but due to lack of some resource these cannot be incorporated in the study. So Further study can be done with the inclusion of wind speed, holiday, precipitation, and large number of previous season load data. Market price has also an indirect effect on load forecasting so it can also be included as an important variable. Recent research on demand side management enhancements have been applied to electrical energy consumers. The load curve of these users may have some new characteristics. Also Future work can focus on the load forecasting of the demand side management users.

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