A Novel Approach to Short – Term Load Forcasting using Fuzzy Network

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Abstract – Load prediction is important for planning and function in energy organization. It enhances the Energy efficient with consistent operation of a power system. The energy abounding through utilities meets the load as well as the energy lost in the system is ensured via this tool. As in power system the next day's power production must be planned each day. The day-before small term load prediction/ forecasting (STLF) is a essential daily duty for power transmit. Small period load prediction is required for unit dedication, economic allocation of generation, maintenance schedules. At present study gives a solution methodology using fuzzy logic for short term load forecasting. Fuzzy logic methods is implemented on weather sensitive data with historical load data for forecasting the load.

Keywords-- Short term load forecasting, fuzzy logic, membership function, Absolute percentage error.

Introduction

1.1 OVERVIEW

Load forecasting is the guess of upcoming loads of a power system. Electric load forecasting, otherwise short period load forecasting, comes under a range of synonyms: electricity load forecasting; electricity require forecasting; expenditure forecasting; electricity load prediction; load require; power require; load require prediction; and load estimation etc.

Correctness in electricity load forecasting is essential in power system development and function with also will help market participants minimize running cost and develop a more dependable energy supply device (Quaiyum et al 2011).

The major problem of the planning is the require awareness in the future. Basic operating functions like as hydro power with thermal power unit commitment, economic dispatch, fuel scheduling and unit maintenance may be performed professionally with an accurate prediction. Load forecasting is too imperative for contract evaluations as well as evaluations of different financial commodities on energy pricing offered through a de regulated market. Power system designers use various methods to optimally plan, monitor, as well as operate different aspects of presents complicated power systems. Some of those methods are economic dispatch, unit commitment, state estimation, automatic generation control, security analysis, optimal power flow, and load forecast.

Perfect short-term load forecasting (STLF) has an important contact on power system functioning efficiency. Various operating decisions are depends on such forecasts, including actual time generation control, security analysis, spinning reserves allotment with also energy transactions scheduling.

1.2 Objective of the Study

Load demand based on various parameters like as variation in ambient temperature, wind velocity, humidity, precipitation with also cloud cover. As electricity demand is closely subjective through those climatic parameters, there is similarly to be an impact on demand patterns. For each hour load demand based on these crucial role parameters.

In the past decade, various methods have been used for demand forecasting. Some of these methods are: the time series model, exponential smoothing method, state space method, and linear regression model, along with knowledge based approach. These methods have some drawbacks such as inaccurate calculation, complexity in modelling processes, numerical instability, and necessity of large historical database, with also demand of high human knowledge.

The work presented here will be completed into following steps:

- Classification of Data - For this work consider training and testing the hourly load, hourly temperature and hourly humidity are considered.
- Collection of Data - The hourly load data are collected from Madhya Pradesh Vidyut Vitran Company Jabalpur. The hourly weather data are collected from website data.gov.in
- Training and Testing of the System - For the training and testing of the system consider April 2016 data i.e. hour of the day, temperature and humidity.

II- LITERATURE REVIEW

The various study have been carried out by different researchers, some of them are as follows:

- ***"Neural Network with Fuzzy Set-Based Classification for Short-Term Load Forecasting" by M. Daneshdoost, Senior Member, IEEE, IEEE Transactions on Power Systems, Vol. 13. No. 4. November 1998***
  A multi-layered feel forward ANN combined with the fuzzy set-based classification technique for short-term electric load forecasting has been proposed in this paper. The hourly data was classified into classes based on the fuzzy set representation of two weather variables; dry-bulb temperature and relative humidity. The classification is based on the fact that the power system load is heavily influenced by the weather condition.
- ***"Very Short-Term Load Forecasting Using Artificial Neural Networks" by Wiktor Charytoniuk, Member: IEEE, and Mo-Shing Chen, Fellow, IEEE, lEFF TRANSACTIONS ON POWR SYSTEMS, VOL. IS. NO. I, FEBRUARY 2000***
  In a deregulated, competitive power market, utilities tend to maintain their generation reserve close to the minimum required by an independent system operator. This creates a need for an accurate instantaneous-load forecast for the next several dozen minutes. This paper presents a novel approach to very short-time load forecasting by the application of artificial neural networks to model load dynamics. The proposed algorithm is more robust as compared to the traditional approach wilier actual louds are forecasted and used as input variables. It provides more re- liable forecasts, especially when the weather conditions are different from those represented in the training data.
- ***"Short-Term Load Forecasting Methods: An Evaluation Based on European Data" by James W. Taylor and Patrick E. McSharry, Senior Member, IEEE, IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 22, NO. 4, NOVEMBER 2007***
  This paper used intraday electricity demand data from ten European countries as the basis of an empirical comparison of univariate methods for prediction up to a day-ahead. A notable feature of the time series is the presence of both an intraweek and an intraday seasonal cycle.
- ***"A Novel Hybrid Method for Short Term Load Forecasting using Fuzzy Logic and Particle Swarm Optimization" Amit Jain, Member, IEEE, M. Babita Jain, Member, IEEE and E. Srinivas, 2010 International Conference on Power System Technology***
  Load forecasting has become a very crucial technique for the efficient functioning of the power system. This paper presents a methodology for the short term load forecasting problem using the similar day concept combined with fuzzy logic approach and particle swarm optimization. To obtain the next-day load forecast, fuzzy logic is used to modify the load curves of the selected similar days of the forecast previous day by generating the correction factors for them. These correction factors are then applied to the similar days of the forecast day.
- ***"Short Term Load Forecasting using Fuzzy Adaptive Inference and Similarity" by Amit Jain, E. Srinivas, Rasmimayee Rauta***
  The main objective of short term load forecasting (STLF) is to provide load predictions for generation scheduling, economic load dispatch and security assessment at any time. Thus, STLF is needed to supply necessary information for the system management of day-to-day operations and unit commitment. This paper presents a forecasting method based on similar day approach in conjunction with fuzzy rule-based logic.

III- ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM & FUZZY

3.1 About ANFIS

The acronym ANFIS is Adaptive Neuro - Fuzzy Inference System. Which is an integrated system, comprising of fuzzy logic with Neural Network was used to model the upcoming hour load, since it can address with solve problems correlated to randomness, non-linearity along with uncertainty of data. ANFIS is one of the artificial intelligent techniques that could be used in electric load forecasting. ANFIS is a hybrid system which combines the human reasoning style of fuzzy logic with the connectionist as well as learning technique of neural network.

The model obtained with neural network is not understandable in terms of physical parameters (black box model) and it is impossible to interpret the result in terms of natural language. On the other hand, the fuzzy rule base consists of if-then statements that are almost natural language, but it cannot learn the rules itself. To obtain a set of if-then rules two approaches are used.

First, transforming human expert knowledge and experience, and second, automatic generation of the rules the second method is fully investigated. The fusion of neural networks with fuzzy logic in neuro-fuzzy models achieves readability along with and learning ability i.e. extracting rules from data at once. On 1993, Roger Jang developed the ANFIS technique that could overcome the shortcoming of the ANNs and fuzzy systems.

ANFIS is constructing a fuzzy inference system (FIS) whose membership function parameters are tuned using either a back propagation algorithm or hybrid method (which is a combination of back propagation and least squares method). FIS is the process of formulating the mapping from a given input to an output using fuzzy logic. ANFIS are a class of adaptive networks that are functionally identical to fuzzy inference systems.

A fuzzy inference system consists of fuzzy rules and membership functions and fuzzification and defuzzification operations as shown in figure 3.1.

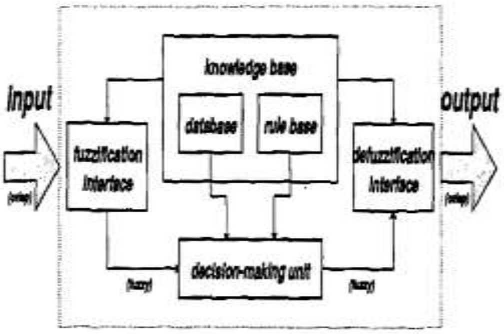

Figure 3.1Components of fuzzy inference system

IV - RESULT AND DISCUSSION

General:

This Chapter comprises in two different section. First section is for Fuzzy results and another for results obtained by ANFIS.

4.1 FUZZY RESULT

Fuzzy logic is an approach to computing based on "degrees of truth" rather than the usual "true or false" (1 or 0) Boolean logic on which the modern computer is based.

Table 4.1 shows the actual load, forecasted load and also the percentage error in the forecasted load. The data of time, temperature and humidity are used as input. Load Data obtained from Madhya Pradesh Vidyut Vitran Company Jabalpur and Weather Data is collected from website data.gov.in The load forecast is done for the 20/4/2016 Sunday.

One of the main characteristics of fuzzy model is the development of the rules. In this section, rules development which relates the fuzzy input and the required output are presented. Figure 4.1 shows the whole structure of fuzzy logic system included input, reasoning rules and also the proposed output. The inference rules relate the input to the output and every rule represents a fuzzy relation.

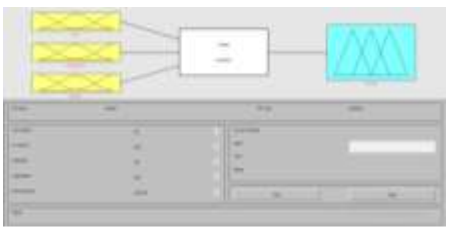

Figure 4.1 Fuzzy system structure

Figure 4.2 Triangular membership function for time

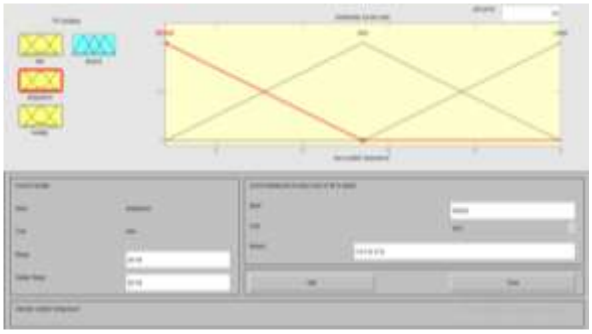

Figure 4.3 Triangular membership function for forecasted temperature.

Figure 4.3 shows temperature divided into three triangular membership functions which are as follows: medium, high and very high. Lower Temperature is not consider because training and testing data is summer season (April month). Figure 4.4 shows the Humidity which is divided into three triangular membership functions which are as follows: Dry,Humid and Very Humid.

Figure 4.4 Triangular membership function for Humidity.

Figure 4.5 shows forecasted load (output) divided intothree triangular membership functions which are as follows: Low, medium and high.

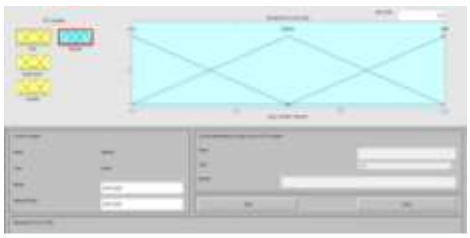

Figure 4.5 Triangular membership function for forecasted load.

Fuzzy Rule Base Load Forecast: This part is the heart of the fuzzy system. The heuristic knowledge of the forecasted is stored in terms of "IF-THEN" rules. It sends information to fuzzy inference system, which evaluates the gained information to get the load forecasted output. In this study the 78 fuzzy rules are used. Some of the rules are as follows:

Figure 4.6 Fuzzy – Rule Base

The Figure 4.8 shows how the fuzzy system in MATLAB toolbox which works for the sample inputs.

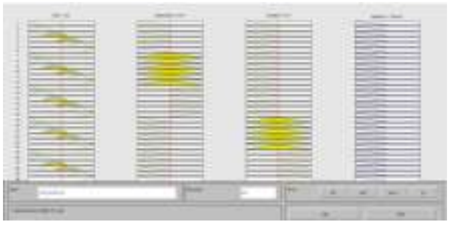

Figure 4.7Defuzzified output for testing data.

4.2 ANFIS RESULT-

The data of time, temperature and humidity are used as input. Load Data obtained from Madhya Pradesh VidyutVitran Company Jabalpur and Weather Data is collected from website data.gov.in.The summer load data of April 2016 is selected for this work. Table 4.2 shows the different case and it's Mean absolute percentage error.

Table 4.2 Different case and it's Mean absolute percentage error

S. NO.	CASE	TRAINING DATA	TESTING DATA	MEAN ABSOLUTE PERCENTAGE ERROR
1.	CASE-1	1/04/2016 - 19/04/2016	20/04/2016 (SUNDAY)	4.371
2.	CASE-2	1/04/2016 - 19/04/2016	21/04/2016 (MONDAY)	4.810
3.	CASE-3	1/04/2016 - 19/04/2016	22/04/2016 (TUESDAY)	4.556
4.	CASE-4	1/04/2016 - 19/04/2016	23/04/2016(WEDNESDAY)	5.2
5.	CASE-5	1/04/2016-19/04/2016	24/4/2016 (THURSDAY)	3.768
6.	CASE-6	1/04/2016-19/04/2016	25/4/2016 (FRIDAY)	[illegible]
7.	CASE-7	1/04/2016-19/04/2016	26/4/2016 (SATURDAY)	4.047

CASE-1

In case-1 Training data set is considered from first three week of April (01/04/2016 – 19/04/2016) and Tested on Sunday, 20/04/2016. In this case, a three input (Hours of the day, Temperature and Humidity) 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 3 for inputsummer temperature (like medium, high and very high) and membership function is 3 for input humidity (like dry, humid and very humid) and process is completed in 10 epochs. A Mean absolute percentage error is 4.371%.

ANFIS info:
The following information is considered for the Results
Number of nodes: 138
Number of linear parameters: 54
Number of nonlinear parameters: 24
Total number of parameters: 78
Number of training data pairs: 456
Number of checking data pairs: 0
Number of fuzzy rules: 54

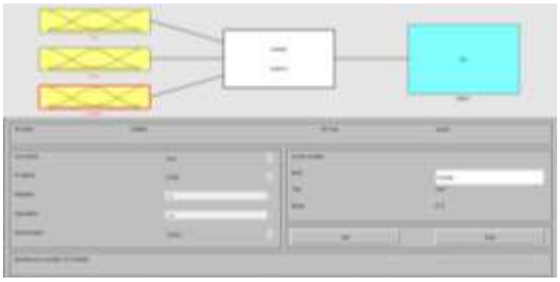

Figure 4.8 FIS Editor: Sunday

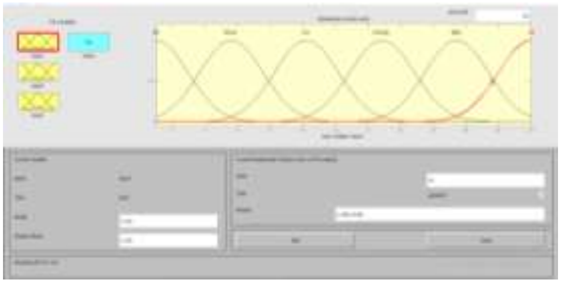

Figure 4.9 Membership function: Time

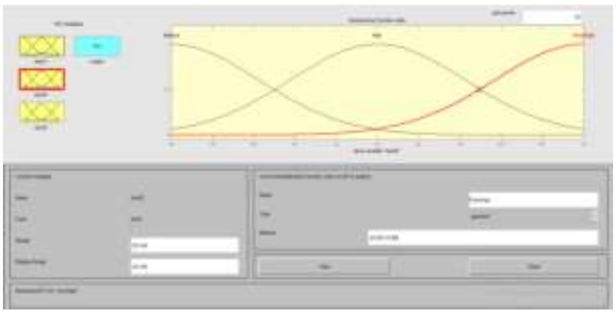

Figure 4.10 Membership function: Temperature

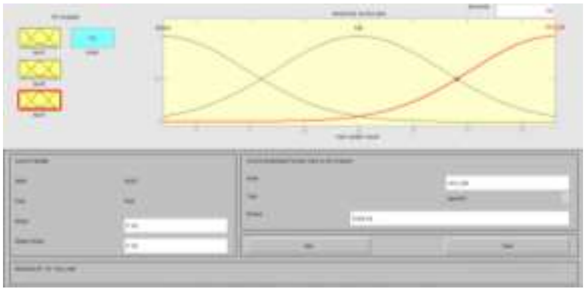
Figure 4.11 Membership function: Humidity

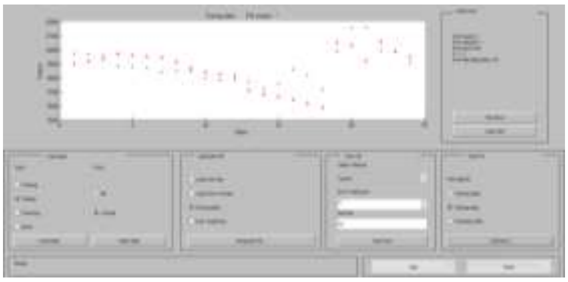
Figure 4.12 Forecast output

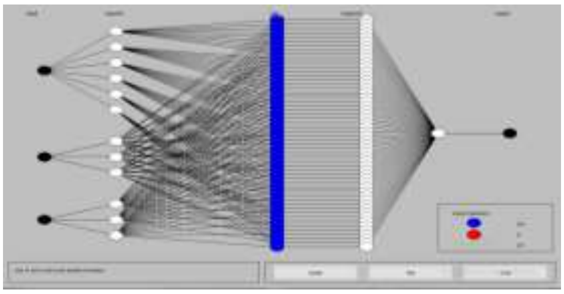
Figure 4.13 Structure

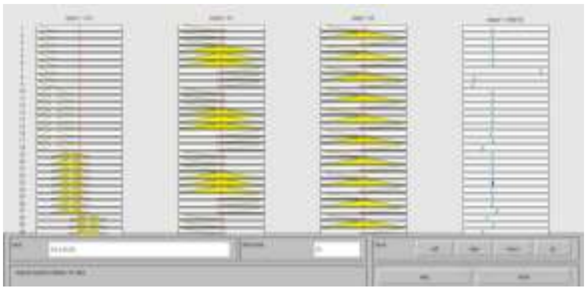
Figure 4.14 Rule Viewer

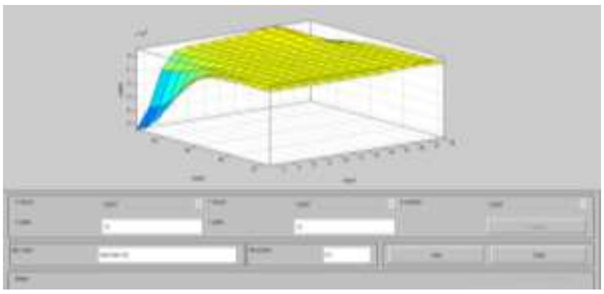
Figure 4.15 Surface


Figure 4.16 Rules

CASE-2

In case-2 Training data set is considered from first three week of April (01/04/2016 – 19/04/2016) and Tested on Monday, 21/04/2016. In this case take a three input (Hours of the day, Temperature and Humidity) 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 3 for input summer temperature (like medium, high and very high) and membership function is 3 for input humidity (like dry, humid and very humid) and process is completed in 70 epochs. A Mean absolute percentage error is 4.816 %.

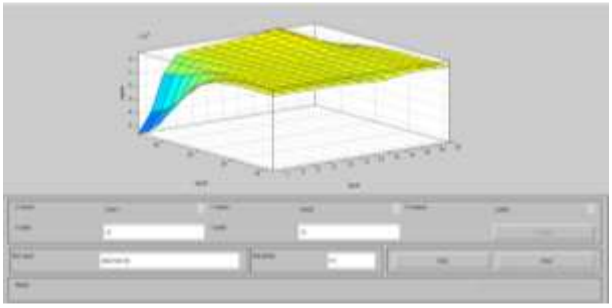
Figure 4.17 Surface

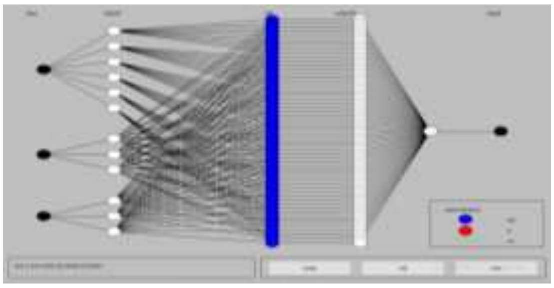
Figure 4.18 Structure

CASE-3

In case-3 Training data set is considered from first three week of April (01/04/2016 – 19/04/2016) and Tested on Tuesday, 22/04/2016. In this case take a three input (Hours of the day, Temperature and Humidity) 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 3 for inputsummer temperature (like medium, high and very high) and membership function is 3 for input humidity (like dry, humid and very humid) and process is completed in 3 epochs. A Mean absolute percentage error is 4.536 %.

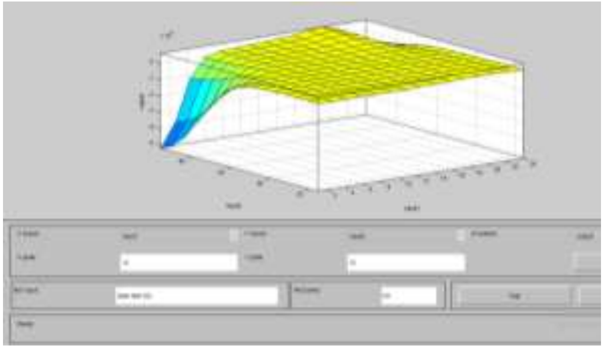

Figure 4.19 Surface

CASE-4

In case-4 Training data set is considered from first three week of April (01/04/2016 – 19/04/2016) and Tested on Wednesday, 23/04/2016. In this case take a three input (Hours of the day, Temperature and Humidity) 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 3 for inputsummer temperature (like medium, high and very high) and membership function is 3 for input humidity (like dry, humid and very humid) and process is completed in 3 epochs. A Mean absolute percentage error is 9.2 %.

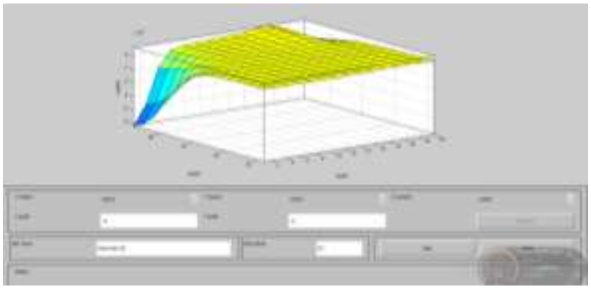

Figure 4.20 Surface

CASE-5

In case-5 Training data set is considered from first three week of April (01/04/2016 – 19/04/2016) and Tested on Thursday, 24/04/2016. In this case take a three input (Hours of the day, Temperature and Humidity) 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 3 for inputsummer temperature (like medium, high and very high) and membership function is 3 for input humidity (like dry, humid and very humid) and process is completed in 500 epochs. A Mean absolute percentage error is 2.768 %.

CASE-6

In case-6 Training data set is considered from first three week of April (01/04/2016 – 19/04/2016) and Tested on Friday, 25/04/2016. In this case take a three input (Hours of the day, Temperature and Humidity) 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 3 for inputsummer temperature (like medium, high and very high) and membership function is 3 for input humidity (like dry, humid and very humid) and process is completed in 520 epochs. A Mean absolute percentage error is 3.677 %.

CASE-7

In case-7 Training data set is considered from first three week of April (01/04/2016 – 19/04/2016) and Tested on Saturday, 26/04/2016. In this case take a three input (Hours of the day, Temperature and Humidity) 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 3 for inputsummer temperature (like medium, high and very high) and membership function is 3 for input humidity (like dry, humid and very humid) and process is completed in 450 epochs. A Mean absolute percentage error is 4.047 %.

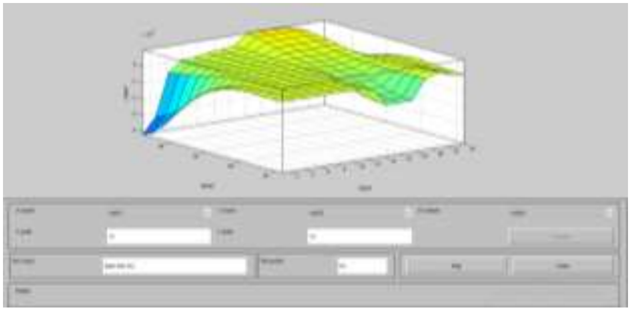

Figure 4.21 Surface

4.3 DISCUSSION

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. In the restricted electricity market, the key power system functional activities some of them are priced-based unit commitment (PBUC), energy interchange, and adequate power reserves rely heavily on a forecasting outcomes with answerable accuracy. Also Equally, STLF is also necessary, especially for big or Large power users (LPUs), to manage their notified maximum demands (NMD) and perhaps even better their expansion plans. The FIS output of this work is compared to the actual load, and evaluation is done by statistical Mean of Absolute Percentage Error (MAPE). MAPE error is one of the main criteria describing the forecast method accuracy level. The model shows relatively good forecasting performance. As the error becomes smaller, the load model becomes more acceptable for the purposes of load forecasting.

Figure 4.69 is the comparison of ANFIS and Fuzzy result for Sunday 20/4/2016. It is observe that ANFIS is definitely superior to fuzzy logic algorithm as it inherits adaptability and learning. ANFIS output is better than fuzzy output.

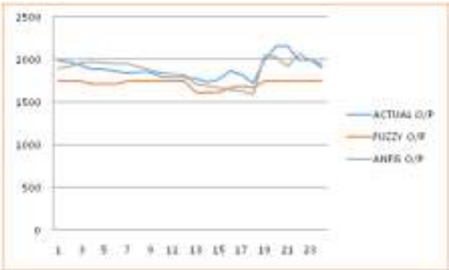

Figure 4.69 Comparison of Actual ANFIS and Fuzzy Result

Conclusion

As electricity demands have deregulated over the last some years, precise load forecasts have become a essential part of a utility's long, medium, and short-term generation with also procurement planning. An incorrect load forecast can has severe penalty for customers in the form of higher rates. At present study fuzzy along with ANFIS methodology for short term load forecasting is presented. ANFIS is definitely superior to fuzzy logic algorithm as it inherits adaptability with learning. The learning period of ANFIS is too short than Fuzzy logic case. It means that ANFIS reaches to the target more early than fuzzy logic. In training of the data, ANFIS gives results with the least of total error as compared to other techniques. This shows that the best learning method is ANFIS among the all other techniques.

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