ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 12, December 2013

LOAD FORECASTING OF ADAMA UNIVERSITY BY IMPLEMENTING FUZZY LOGIC CONTROLLER

SUNIL KUMAR J[1], ARUN KUMAR.P[2], SULTAN F. MEKO[3], DAWITLEYKUEN [4],MILKIAS BERHANU [5]

Assistant Professor, Dept of Electrical and Computer Science Engineering, Adama Science and Technology University, Adama, Ethiopia[1235]

Assistant Professor, Dept of Electrical and Computer Science Engineering, Jimma institute of Technology University, Jimma, Ethiopia[4]

ABSTRACT: Load forecasting is very important task in for the developing countries, to utilize the power more efficiently. In the developing countries like India, Ethiopia, Ghana, there is lot of power is wasting in the generation, and transmission and distribution. It is due to mainly lack of forecasting the daily load. In this paper we had conducted a practical experiment to estimate load demand of Adama Science and Technology University, Ethiopia. In this paper we are using the short term load forecasting. The data we collected from the ASTU is the previous year data. To analysis the results we used the Mandani model in the Fuzzy logic methods. To reduce the error of the load forecasting of the fuzzy method has been used with the Artificial Neural Network. The error range is reduced nearly 3%. The programs have been ruined in the Matlab environment.

Keywords: Neural Network, Fuzzy logic, Load forecasting.

I INTRODUCTION

FORECASTING for vision load demand prerequisite is the most imperative key for power system planning. The ability of the generation, transmission and distribution capacities are strictly dependant on the precise energy and load forecasting for that system Power system expansion planning starts with a forecast of anticipated future load requirements. Estimates of both demand and energy requirements are crucial to valuable system planning. The term forecast refers to projected load requirements determined using a systematic process of defining future loads in sufficient quantitative detail to permit important system expansion decisions to be made. The Energy Management System demands accurate load forecasting and short term Load Forecasting provides better and truthful results [1].

To predict the load forecasting there are many types of method are there in the present industry. The fore casting may do based on the time period. Long Term Forecasting, in this type of forecasting the forecasting period is long may be for 10 years. The planning of maintenance, scheduling of the fuel supply etc. calls for medium term load forecast. The medium term load forecast covers a period of a few weeks. It provides the peak load and the daily energy requirement. Another type of forecasting is Short Term Forecasting. Short term Forecasting gives the accurate values to predict the load demand. This short term forecasting covers to predict the load for a short term period of one week. The method that has been hassled upon is Short term load forecasting. A number of methods and techniques have already been worked out for prediction of load such as Artificial Neural Networks (ANN), Fuzzy Logic, and Regression Methods etc. Among all these Neural Networks are having the properties of sluggish convergence time and deprived ability to process a large number of variables at a time. In a power system with large geographical area, the weather and electricity demand diversity across the entire area is a key issue that influences the forecasting accuracy. In general the load will fluctuate more based on the weather conditions of the area. These weather conditions give the non linear behavior of the load. In day times the load is different from the night times, also in the week days and the normal days, the seasons will highly effect the load variations.

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II. THE WORK

In this study, a short term load forecasting method using fuzzy logic has been developed and a tender to the progression of the study with the use of artificial neural network (ANN) in different ways has been put up. A part of complete and generalized software by means of Fuzzy Logic has been attempt to put into survival to forecast electrical load for domestic as well as commercial areas such as industries, institute or residential colonies etc. The input parameters are Day's minimum temperature, Day's maximum temperature, season, day capacity, rain, daylight intensity (Cloudy). Day's minimum temperature is a temperature at what time operational hours start. All these parameters are put as input to fuzzy system and the inputs are first of all level in the requisite value restrictions and fuzzified. preceding data (historical data or heuristic knowledge) which has already been stored in data bottom is used for deduction. Rule base is designed to follow the heuristic knowledge according to the membership functions of a variety of inputs. As in Fig. 1, Degree of Membership for different input parameters is establish out in the range [0-1] and then defuzzified to get the crisp output which is then de-scaled to the required units and range [8], [10].

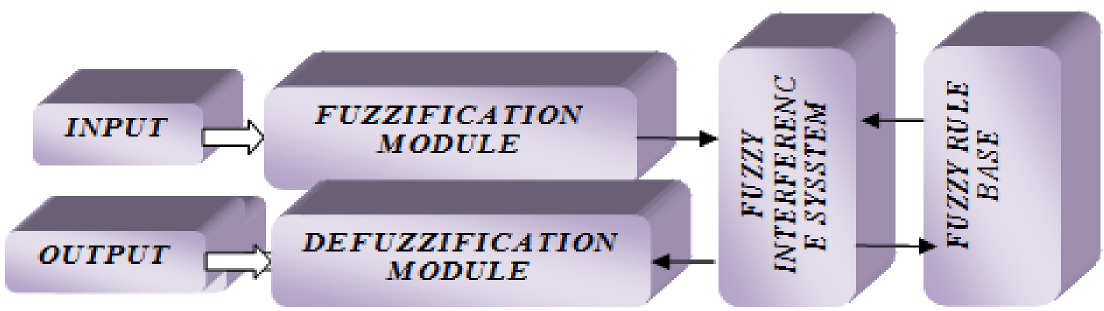

Fig. 1.Working Process of Fuzzy Logic Controller to the System.

The main work we under this section is collecting the data of the university load conditions and we had taken the temperature conditions also by keeping some temperature equipments, to find the temperature conditions.

III. HISTORICAL DATA AND KEY FACTORS

A good quality of past data for contribution parameters for the last few years has been stored in data base organization system (DBMS) for exact load forecasting [5]. Short term load forecasting mostly depends on the subsequent circumstances:

- Utilization of electric power in a day
- Temperature and weather conditions

Though the day capacity can be defined as working day or non working day (weekend or holiday). But as per this learn weekend and holiday are put in the similar category at what time no work or negligible work is done. One more category as special day has been considered. This is the category when work is done after usual 8 operational hours of the day (means if work is done for 9 Hrs. in a day shows one complete normal day and 1 Hr. of particular day) or 9 Hrs. of particular day depending on the type of work.We had considered the working hours of the ASTU in to two types. One based on the students learning process. First we consider teaching class only which include Theory and tutorials. The power consumption equipments are lights, projectors, and fans. And second session is practical sessions, which includes labs and workshops.

- the type of work (either Theory or Practical)

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- Day elongation

So day capacity can be calculated as

$$DC = \sum_i Ti * D \qquad \text{-- (1)}$$

Two main factors have be distinct to decide climate circumstances – dull and/or Rainy weather. Cloudy weather gives an important effect of the day light intensity income more the clouds, lesser will be the day light concentration, more will be the utilization of electrical energy. These factors somehow are related to day's minimum temperature and day's greatest temperature. In fact, there can be a contrast between two working days with alike day ability but dissimilar climate conditions; load obsessive on both the days will be different. This can also occur that for two days, one is operational and additional is non working with dissimilar weather conditions, the load consumed is same [6].

IV. LOAD FORECASTING

A. Fuzzification

Fuzzification is the process of making a crisp quantity fuzzy. We do this by simply recognizing that many of the quantities that we consider to be crisp and deterministic are actually not deterministic at all: They carry considerable uncertainty. If the form of indecision happens to arise because of imprecision, ambiguity, or vagueness, then the variable is probably fuzzy and can be represented by a membership function. In the real world, hardware such as a digital voltmeter generates crisp data, but these data are subject to experimental error. Fuzzy linguistic variables are used to stand for a variety of input as well as output parameters as the member of fuzzy sets. In arrange to articulate the fuzziness of in order, this manuscript create an agreement of fuzzy subsets for dissimilar inputs and outputs in total universe of dialogue as membership functions [9]. Membership functions can be symmetrical or asymmetrical. They are typically defined on one-dimensional universes, but they certainly can be described on multidimensional (or *n*-dimensional) universes. The association between several inputs and output may be non linear but linear membership functions have been used for straightforwardness and only the membership function for seasons is full as ridge-shaped membership function such as gbell mf, gauss mf, and gauss2mf. As in Fig. 2,

The Day's Minimum Temperature and Maximum Temperature are represented as fuzzy subset [Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH)].

The linguistic variables of Day Capacity as [Minimum (min), Very Low (VL), Low (L), Medium (M), High (H), Very High (VH), Maximum (max)].

The fuzzy subset for day capacity is [Very Low (VL), Low(L), Normal (N), High (H), Very High (VH)].

The Season's fuzzy subset is given with the names of season as [Spring, Summer, Autumn, Winter].

The rain forecast has been given by fuzzy subset [No Rain, Drizzling, Normal Rain, Heavy Rain].

Similarly, the output factor load also has been assigned as fuzzy subset with membership functions [Minimum (min), very low (VL), Low (L), medium (M), High (H), Very High (VH), Maximum (max)].

B. Fuzzy Rule Base

This is the part of fuzzy system where heuristic knowledge is stored in terms of "IF-THEN Type" Rules. The rule base is used to send information to fuzzy inference system (FIS) to process through inference mechanism to numerically evaluate the information embedded in the fuzzy rule base to get the output. The rules are like:

- IF (Min Temp is M) and (Max Temp is L) and (Day Light-Intensity (Clouds) is VH) and (Season (Day Number) is SUMMER) and (Rain is NORMAL) THEN (Output Load is H).
- IF (Min Temp is H) and (Max Temp is H) and (Day Light- Intensity (Clouds) is L) and (Season (Day Number) is AUTUMN) and (Rain is DRIZZLING) THEN (Output Load is H).
- IF (Min Temp is VL) and (Max Temp is VL) and (Day Light-Intensity (Clouds) is H) and (Season (Day Number) is WINTER) and (Rain is NO_RAIN) THEN (Output Load is MAX).

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ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

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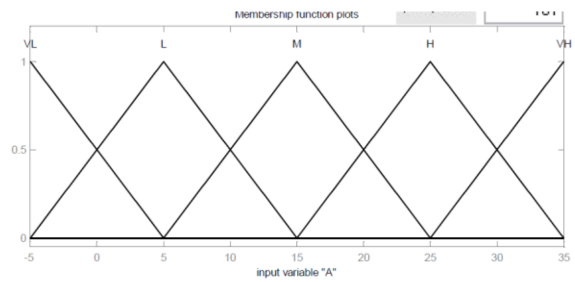
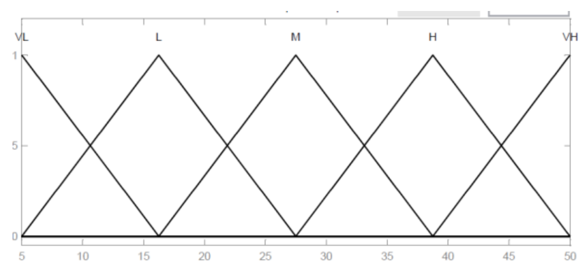
Vol. 2, Issue 12, December 2013

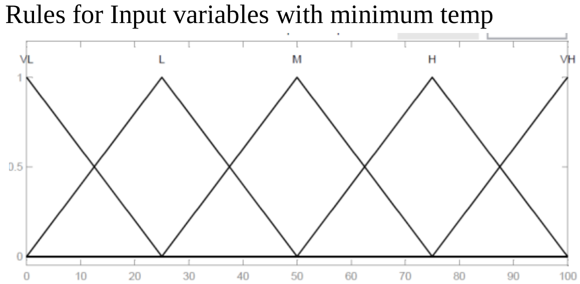
- IF (Min Temp is H) and (Max Temp is H) and (Day Light-Intensity (Clouds) is L) and (Season (Day Number) is SPRING) and (Rain is NO_RAIN) THEN (Output Load is M).
- IF (Day Type (Day Capacity) is MIN) and (Season (Day Number) is SUMMER) THEN (Output Load is MIN).



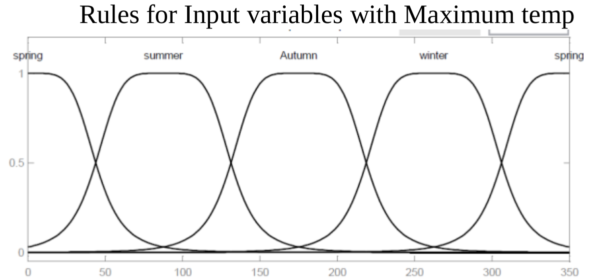
Rules for Input variables with minimum temp



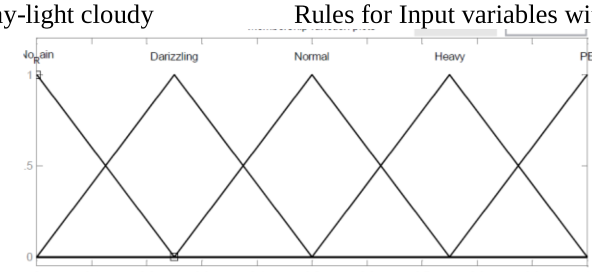
Rules for Input variables with Maximum temp



Rules for Input variables with Day-light cloudy



Rules for Input variables with seasons with day number



Rules for Input variables with rain

Fig. 2. Membership Functions for different input variables Day's MinTemp, Day's Max Temp, Day Light Intensity, Day Type, Season, and Rain.

V. RESULTS

Table 1 shows the actual load, forecasted load and also the % error in the forecasted load for the data processed and calculated in the month of JUNE, 2005 (E.C). The % error of this study is calculated as

$$\%\text{Error} = \frac{Actual\ \ Load\ \ of\ \ ASTU - Forecast\ \ Load\ \ of\ \ ASTU}{Actual\ \ Load} * 100$$

The forecasted load compared with the actual load gives the maximum percentage error 4.04814% and minimum percentage error calculated is -0.38425%. The forecasted load for the month of October has been shown for the reason that this is the mid time of a working session in an Adama Science and Technology University in Ethiopia. Moreover, the change of season also takes place in this duration.

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ISSN (Online): 2278 – 8875

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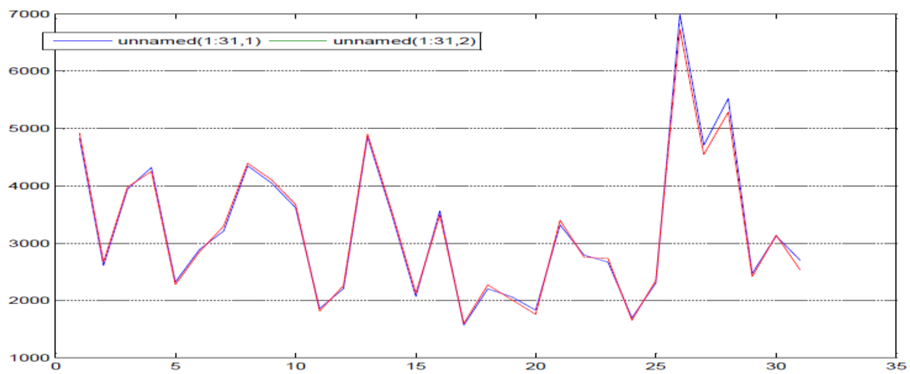

Fig. 3. Comparison of Actual Load and Forecasted Load for October, 2006 (E.C)

Both the results have been compared graphically, as in Fig. 3, showing the minute variations in the actual and forecasted loads for the same session given in Table I.

TABLE I
ERROR (%) IN LOAD FORECASTING FOR OCTOBER, 2006(E.C)

S.No	Actual Load	Forecast Load	Error	% Error
1	4834	4921	-0.01799751	-1.79975
2	2604	2665	-0.02342549	-2.34255
3	3937	3977	-0.01016002	-1.01600
4	4320	4251	0.01597222	1.597222
5	2320	2276	0.01896551	1.896552
6	2883	2843	0.01387443	1.387444
7	3212	3296	-0.02615193	-2.61519
8	4349	4394	-0.01034720	-1.03472
9	4044	4104	-0.01483679	-1.48368
10	3617	3671	-0.01492954	-1.49295
11	1855	1812	0.02318059	2.318059
12	2206	2259	-0.02402538	-2.40254
13	4854	4902	-0.00988875	-0.98888
14	3496	3547	-0.01458810	-1.45881
15	2066	2121	-0.02662149	-2.66215
16	3563	3490	0.02048835	2.048835
17	1566	1596	-0.01915708	-1.91571
18	2200	2270	-0.03181818	-3.18182
19	2061	2012	0.02377486	2.377487
20	1828	1754	0.04048140	4.04814
21	3319	3397	-0.02350105	-2.35011
22	2788	2753	0.01255380	1.25538
23	2667	2731	-0.02399700	-2.3997
24	1693	1651	0.02480803	2.480803

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25	2301	2353	-0.02259887	-2.25989
26	6991	6734	0.03676155	3.676155
27	4707	4543	0.03484172	3.484173
28	5520	5286	0.04239130	4.23913
29	2466	2412	0.02189781	2.189781
30	3123	3135	-0.00384245	-0.38425
31	2701	2532	0.062569419	6.256942

VI. THE PROPOSED SCHEME

A single technique in itself is not sure to produce the good results, but it can be merged or supplemented with other methods also. Experiments were performed on some of the values using Artificial Neural Network (ANN) with Fuzzy Logic, giving a little reduction in the error but were not consistent due to lack of optimally trained network. In the proposed scheme, artificial neural network (ANN) can be added with fuzzy logic to produce better results in different configurations, provided, ANN is a trained network. Though ANN is slow in calculations and can not process number of inputs in large number of stages (hidden layers) [4], [7]. The two ways with which ANN can be added to fuzzy logic are shown as in Fig. 4 and Fig. 5.

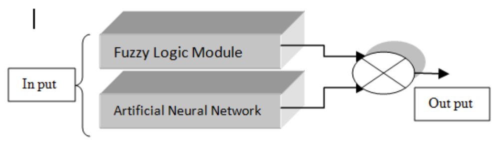

Fig. 4. Fuzzy Logic and Artificial Neural Network processing on same data separately to produce results.

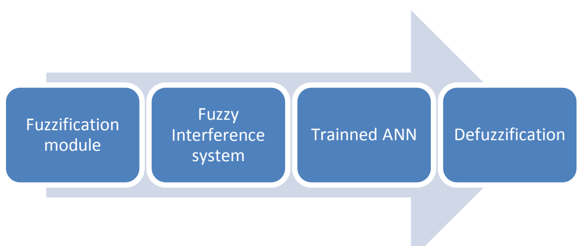

Fig. 5. Interfacing with fuzzy and Artificial Neural Network

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ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

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BIOGRAPHY

Mr.Sunil kumar.J was born in Tirupathi, India. He received B.Tech in Department of Electrical and Electronics from Anna Univeristy, Chennai, in 2006 and M.Tech from Sri Venkateswar University, Tirupathi, in 2011. He is pursuing his PhD in Applications of FACTS devices in the power systems and renewable energy sources. Currently working as a Assistant Professor in Adama science and technology university, Adama. His research interests include Power Systems, Renewable Energy, Fuzzy Logic, Neural Networks, Flexible AC Transmission System (FACTS).Up to now 13 International journals are in credit, 6 International conferences. He is working as a reviewer for many journals like International Journal of Electrical Power & Energy Systems (Elesvier) International Journal of Scientific and Engineering Research, (IJ-ETA-ETS), Global Journal of Researches in Engineering, United States, International Journals of Engineering &Sciences.

Mr. Arun kumar.P born in Guntur India, he received undergraduate in Electrical and Electronics Engineering from JNTUH in 2005, Masters from Acharya Nagarjuna University in 2011 in the field of Power Systems. Currently he is pursuing his PhD in power systems. He is having 7 years of teaching experience, Currently he is working as Assistant professor in Adama Science and Technology University, Ethiopia. His research interests include power systems, Renewable energy and fuzzy logic.

Dr. Sultan F. Meko born in Ethiopia, He is having 10+ years of teaching experience. He is lecture in Electrical and Computer Engineering Department, School of Engineering, Adama Science & Technology University, Ethiopia. His educational background is communication engineering. Presently he is serving as a Dean for school of engineering in Adama Science and Technology University. His research interests include Resource Allocation, Scheduling, and Modeling wired/wireless networks.

Mr.DawitLeykuen born in Ethiopia, He is having 6+ years of teaching experience. He is lecture in Electrical and Computer Engineering Department, School of Engineering, Jimma institute of technology, Ethiopia. His educational background is Electrical power Engineering. Presently he is serving as a Head of the department for electrical and computer science engineering department in Jimma institute of technology. His research interests include Renewable energies, power system operation and control, electrical power transmission and distribution, power quality and reliability

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Mr. Milkias Berhanu Tuka born in, Ethiopia. He is having six years of working experience in Dept of electrical and computer engineering department in Adama science and Technology University.His educational background is Electrical engineering. Currently he is working as a head of department in Adama Science and Technology University. His research interests arepower systems, power electronics, renewable energy, FACTS. .