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Long-term load forecast modelling using a fuzzy logic approach

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ABSTRACT

The importance of long-term load forecasting in the power industries cannot be over-emphasised, as it provides the industries with future power demand that may be useful in generating, transmitting and distributing power reliably and economically. In recent times, many techniques have been used in load forecasting, but artificial intelligence techniques (fuzzy logic and ANN) provide greater efficiency compared to conventional techniques (e.g., regression and time series). In this paper, a fuzzy logic model for long-term load forecasting is presented. A fuzzy logic model is developed based on the weather parameters (temperature and humidity) and historical load data for the town of Mubi in Adamawa state to forecast a year-ahead load. The fuzzy logic model forecast a year-ahead load with a MAPE of 6.9% and efficiency of 93.1%. The result obtained reveal that the proposed model is capable of predicting future load.

1. Introduction

Forecasting is the estimation of the value of a variable (or set of variables) at a future point in time. This definition is adopted from [18]. The main aim of power companies is to provide their customers with a sufficient and reliable power supply [14]. The power they generate, transmit or distribute is very costly and too precious to be wasted. However, load demand is never constant; it fluctuates due to reasons such as variation in weather parameters, breakdown of power facilities as a result of over-usage, limited capacity and lack of proper maintenance. Additionally, the increase in the number of customers cannot be predicted accurately. There may be error in the knowledge of when these challenges and changes will occur. This usually results in a shortage or interruption of the power supply which causes inconveniencies and sometimes losses depending on the classes of consumers. Therefore, load forecasting is an important and useful tool for power companies in terms of operation and planning for the future demand of their customers [1,12]. Also load forecasting remains an indispensable factor for power system planning and evaluating the cost effectiveness of investing in new techniques and strategy for effective power delivery [3,8,11]. The types of load forecasting are classified into four categories [13].

- Very short-term load forecasting: forecasting for few minutes to a few hours.
- Short-term load forecasting: forecasts within a time period of few hours to few days.
- Mid-term load forecasting: forecasting for few weeks to a few months.
- Long-term load forecasting: forecasting within the period of one year to more than one year.

Based on the reasons and needs, any of the above categories can be chosen. In this work, long-term load forecasting is used to forecast future load. In most of the literature several methods of forecasting have been developed. These include linear regression, exponential smoothing, stochastic processes, the ARMA model, data mining models, fuzzy logic and artificial neural network (ANN) [2,4,16]. Among these methods, fuzzy logic and ANN are widely used. However, fuzzy logic seems to take the lead over ANN because of its distinct characteristics [5], for example, when there is a reasonable fluctuation between the weather parameters and load, fuzzy logic can handle it with less forecast error.

Abbreviation: ANN, Artificial Neural Network; PHCN, Power Holding Company of Nigeria; MF, Membership Function; MW, Megawatts; H, Humidity; T, Temperature; FL, Forecasted load; LH, Low Humidity; MH, Medium Humidity; HH, High Humidity; LT, Low Temperature; HT, High temperature; LL, Low Load; ML, Medium Load; HL, High load; APE, Absolute percentage Error; MAPE, Mean Absolute Percentage Error; n, number of sample data.

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In this work, long-term load forecasting for future planning using fuzzy logic is proposed and the following objectives can be achieved; the development of a fuzzy logic simulation model in order to forecast a future load, the development of a fuzzy rule base to enable us determine accurate load forecasting and to confirm the effect of the weather parameters on the electrical load.

1.1. Fuzzy systems

The basic concept of fuzzy set theory was first introduced by Zadeh in 1965 [6]. Fuzzy set theory can be considered as a generalized classical set theory. Normally, in classical set theory an element can either belong to a particular set or not. Therefore, the degree of being a member of that set is its crisp value. However, in fuzzy set theory, the degree of membership of an element can be continuously varied. Fuzzy set maps from the universe of discourse to the close interval $\{0, 1\}$ [17]. The continuous nature of data can be represented by a membership function in fuzzy sets. Fuzzy set theory is one of the dominant technologies in artificial intelligence (AI) and it has broad application in load forecasting. For example, it can model ordinary linguistic variables which may be imprecise or vague in nature at a cognitive level [1,7]. Load forecasting involves many uncertainties, such as the variation in such factors as temperature, humidity, rainfall, wind speed, atmospheric pressure and solar radiation with respect to load, and its value cannot be exactly determined numerically [10]. Therefore, a fuzzy logic approach will be the most suitable method to use under such conditions.

Fuzzy logic is used to map the highly non-linear relationship (using membership function) between the weather parameters and their consequences on the peak load in every month of the year [20]. In this paper, the two parameters of temperature and humidity are used as inputs to the fuzzy logic model while load is an output. The end expectation is that the two weather parameters may have an impact on the load peak as observed in this research.

2. Methodology

2.1. Method of data collection

The data are collected from two places. The weather parameters of temperature and humidity are collected from the meteorological centre of the Department of Geography of Adamawa State University, while the historical load data comes from Power Holding Company of Nigeria (PHCN), a Mubi business unit of Adamawa state.

The block diagram of Fuzzy interface shows how to forecast the future load.

2.2. Fuzzy interface

The fuzzy interface can be actualized using the block diagram of Fig. 1. The weather parameters are fed to the fuzzifier and the output of the fuzzifier and fuzzy rule base enter into the Fuzzy inference engine which is the heart of the system as it processes input data and gives out the forecasted load. The inference system accomplishes the task of forecasting by the use of a fuzzy rule base prepared by the forecaster.

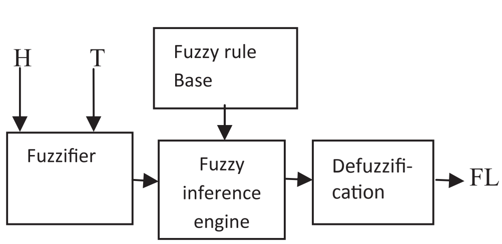

Fig. 1. Fuzzy interface.

In practise, the accuracy of the forecast depends on the cognizance of the forecaster and the prepared rules. The output from the fuzzy inference engine is still fuzzy in nature. It is then converted into a crisp value by defuzzification, which produces the forecasted load.

Figs. 2–4 show the variation in load for the years 2013 and 2014 and their average loads with temperature and humidity. It is observed from the figures that the load increases with an increase in temperature while an increase in humidity does not produced much impact on the load as in [2] where the relationship between load and weather parameters is linear. This may be attributed to the geographical location and the weather conditions of the town of Mubi in Adamawa State. This necessitated the present research.

2.3. Fuzzification of input and output

The first step is to examine the historical data of all the parameters that are used as inputs and outputs. The maximum

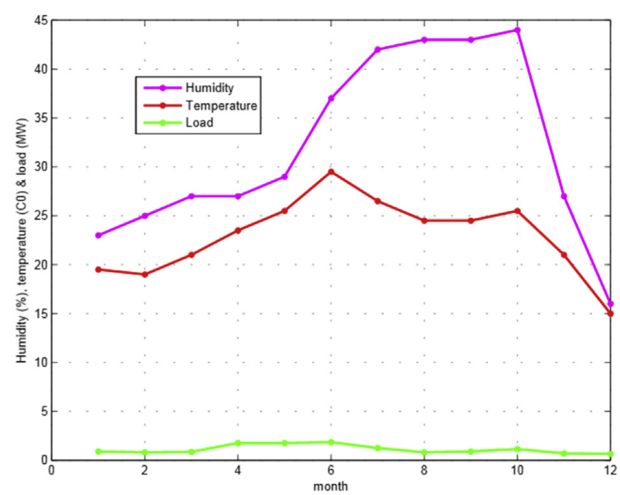

Fig. 2. Load, temperature and humidity vs. month for 2013.

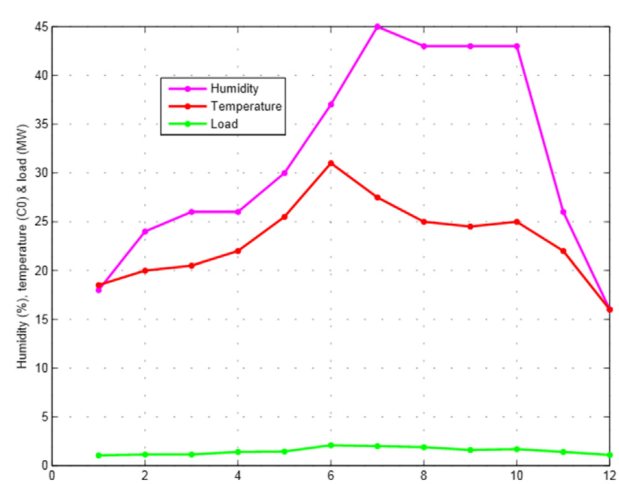

Fig. 3. Load, temperature and humidity vs. month for 2014.

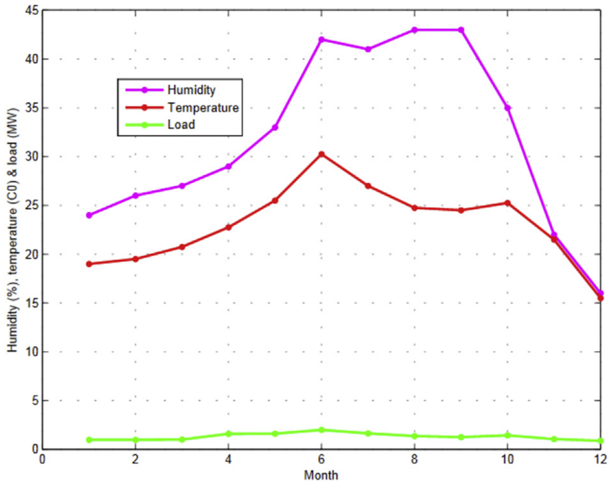

Fig. 4. Average load, temperature and humidity vs. month.

and minimum values of the parameters such as temperature and humidity are obtained and used for the process of fuzzification.

In this work, load is considered as an output while temperature and humidity are input parameters. From the data collected, the following fuzzy sets are classified as Low Load (LL): 0.5 MW–1.0 MW, Medium Load (ML): 1.0 MW–1.5 MW, High Load (HL): 1.5 MW–2.0 MW, while the input parameters are classified as Low Humidity (LH): 16%–26%, Medium Humidity (MH): 27%–38%. High Humidity (HH): 39%–43%, Temperature with range of 15 °C–31 °C is classified as Low Temperature (LT): 15 °C–21 °C and High Temperature (HT): 22 °C–31 °C.

2.4. Assigning of membership function

"Membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value between 0 and 1" [21]. This research considered the load and weather

Fig. 5. Membership function for humidity.

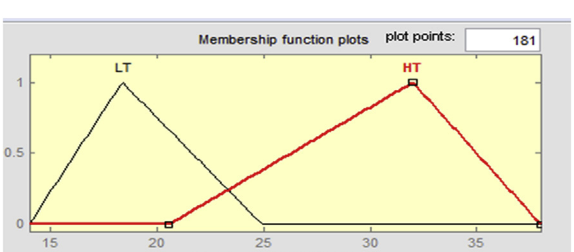

Fig. 6. Membership function for temperature.

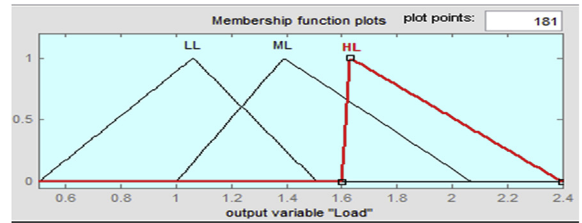

Fig. 7. Membership function of load.

parameters as the fuzzy sets or universe of discourse. These are further classified as low, medium and high and they serve as a subset of the fuzzy sets. A number of membership functions used in fuzzy logic includes the triangular, trapezoidal and bell shapes [15]. In this research a triangular membership function is arbitrarily chosen. To assign the membership function to the various subsets of fuzzy sets, it is observed that the humidity can be best classified in the ranges (15%–32%), (27%–43%), and (41%–50%) as LH, MH and HH, respectively. The temperature is classified as (14 °C–24 °C), (20 °C–38 °C) as LT and HT, and the load is classified as (0.5 MW–1.5 MW), (1.0 MW–2.0 MW), and (1.7 MW–2.4 MW) as LL, ML and HL. These are fully implemented as shown in Figs. 5–7, respectively.

2.5. Fuzzy rule base

This aspect is the most important of the whole work. The forecast output will depend on these rules. The antecedents (input variables) are fed to the fuzzy inference engine and when the rules are applied, the inference system acts on the antecedent and produces the consequences (output). If there are two or more variables to be used as antecedents, fuzzy operators, for example AND, OR and NOT, may be used to combine the variables to form fuzzy sentences. Some of the rules formulated are as follows.

IF (humidity is LH) AND (Temperature is LT) THEN (Load is LL)
IF (humidity is MH) AND (Temperature is LT) THEN (Load is HL)
IF (Humidity is MH) AND (Temperature is HT) THEN (Load is ML)
IF (Humidity is HH) AND (Temperature is HT) THEN (Load is ML).
IF (Humidity is HH) OR (Temperature is HT) THEN (Load is HL)

2.6. Building fuzzy logic models and simulations

Fig. 8 shows a fuzzy logic model. This is developed in the simulink environment in MATLAB (R2014a product of MathWorks Natick, U.S.). As can be seen, two input data are multiplexed and sent into the fuzzy logic controller with the rule viewer and the output is captured on a display.

2.7. Error analysis

The absolute percentage error (APE) and mean absolute percentage error are computed using Equations (1) and (2)

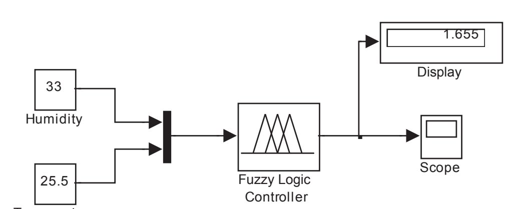

Fig. 8. Simulation of long-term load forecasting using fuzzy logic in Simulink.

$$\text{APE} = \left|\frac{actual(i) - \text{forecast}(i)}{\text{actual}}\right| \times 100 \tag{1}$$

$$\text{MAPE} = \frac{1}{\text{n}} \sum_{i=1}^{n} \left|\frac{\text{actual}(i) - \text{forecast}(i)}{actual(i)}\right| \times 100\% \tag{2}$$

3. Results and discussion

The output of the fuzzy inference system is an aggregate of all the membership functions acted upon by the inference engine. To obtain its crisp equivalent, defuzzification is performed [9,19]. The centroid of area method produces a numerical forecast that is sensitive to all the rules applied. Fig. 8 shows the forecasted output for a sample data set. It is observed after the simulation that for a

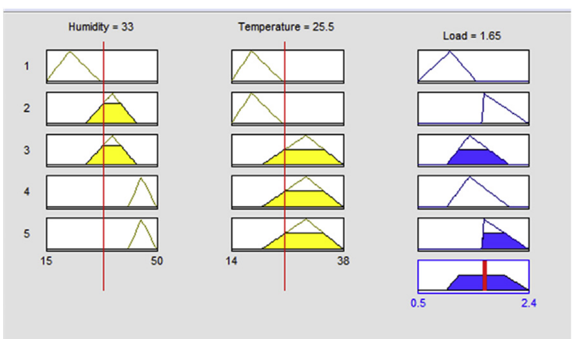

Fig. 9. Defuzzified forecasted output for one sample data set.

Table 1
Humidity, temperature, actual and forecasted load for 2013.

H (%)	T (°C)	Actual load (MW)	Forecasted load (MW)	APE (%)
23	19.50	0.90	0.83	7.89
25	19.00	0.80	0.84	4.50
27	21.00	0.85	0.85	0.45
27	23.50	1.75	1.32	14.84
29	23.50	1.75	1.76	0.57
37	29.50	1.85	1.80	2.70
42	26.50	1.25	1.35	8.00
43	24.50	0.80	1.06	17.77
43	24.50	0.90	1.06	6.00
44	25.50	1.15	1.06	7.83
27	21.00	0.70	0.85	5.75
16	15.00	0.65	0.85	12.80
			MAPE (%)	7.43

Table 2
Humidity, temperature, actual and forecasted load for 2014.

H (%)	T (°C)	Actual load (MW)	Forecasted load (MW)	APE (%)
18	18.50	1.05	1.25	19.00
24	20.00	1.15	1.25	8.00
26	20.50	1.15	1.25	8.00
26	22.00	1.40	1.25	10.00
30	23.50	1.45	1.53	5.00
37	31.00	2.10	2.25	7.00
45	27.50	2.00	1.70	15.00
43	25.00	1.90	1.70	11.00
43	24.50	1.60	1.70	6.00
43	25.00	1.70	1.70	0.00
26	22.00	1.40	1.25	10.00
16	16.00	1.10	1.25	14.00
			MAPE (%)	8.55

Table 3
Average humidity and temperature, and actual and forecasted load.

H (%)	T (°C)	Actual load (MW)	Forecasted load (MW)	APE (%)
24	19.00	0.98	1.04	6.12
26	19.50	0.98	1.04	6.12
27	20.75	1.00	1.05	5.00
29	22.75	1.58	1.29	18.34
33	23.50	1.60	1.65	3.12
42	30.25	1.98	2.03	2.53
41	27.00	1.63	1.53	6.14
43	24.75	1.35	1.38	2.22
43	24.50	1.25	1.38	10.40
35	25.25	1.43	1.38	3.50
22	21.50	1.05	1.05	0.00
16	15.50	0.88	1.05	19.32
			MAPE (%)	6.90

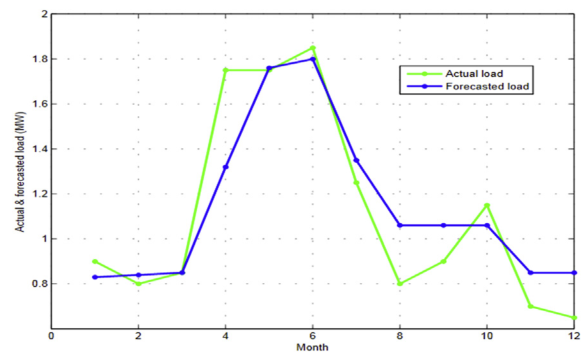

Fig. 10. Month vs 2013 actual and forecasted load.

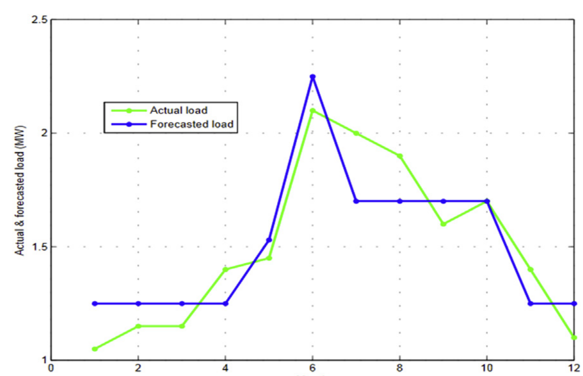

Fig. 11. Month vs. actual and forecasted load for 2014.

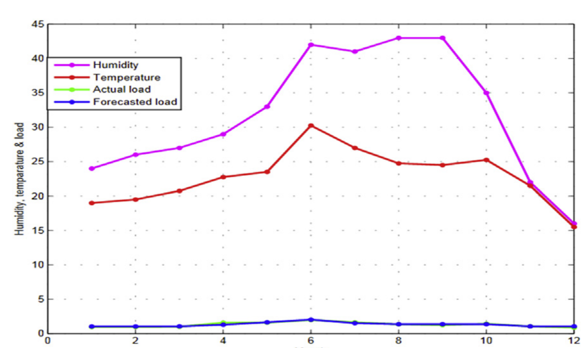

Fig. 12. Month vs. average actual and forecasted load.

humidity of 33% and temperature of 25.5 °C, the forecasted load is 1.65 MW.

Fig. 9 shows the rule viewer which indicates the forecasted load for a sample data set. It is used to view the output of the model as that of Fig. 8.

Tables 1 and 2 show the actual and forecasted load for the years 2013 and 2014, while Table 3 shows the average load and the expected load for a year ahead, and their respective APE is computed using Equation (1) for the sample data. MAPE is computed using Equation (2).

Figs. 10 and 11 shows the graphical representation of the actual and forecasted load in the year 2013 and 2014, respectively, while Fig. 12 shows their average humidity and temperature with actual and forecasted load at the bottom. As it is observe from Fig. 12 that the load increases with increase in temperature. This is clearly shown in the month of June when the maximum load corresponds to the maximum temperature. However, an increase in humidity has less effect on the load. It is also worth mentioning that weather parameters have an effect on the load.

4. Conclusions

In this paper, a fuzzy logic model is proposed and presented as a basis for long-term forecasting. Long-term forecasting plays a very important role in power planning and operation. Reliable forecasting techniques are essential in long-term load forecasting, which this work has demonstrated. This paper only forecasted the load for a year ahead. However, with much historical data, forecasting for more years can be done with intensive study and evaluation of the data. The fuzzy logic model developed for long-term load forecasting presented a very good forecast. A reliably forecasted result is obtained and MAPE is evaluated as 6.9%, which shows the variation of the forecast from the actual load. This difference may be as a result of an inconsistency in the power supply during certain months of the year. However, the accuracy of the prediction is calculated as 93.1%. Thus, the model indicates that it is efficient and capable of forecasting the load with precision.

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