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RESEARCH PAPER

Application of Different Membership Function for Short-term Load Demand Estimation: A Neuro-Fuzzy Approach

A. Y. Sada,*[,1] Asia'u Talatu Belgore,[1] A. F. Shehu,[1] Fatima Balarabe Ilyasu,[1] and S. I. Abba[2,3]

[1]Department of Electrical and Computer Engineering, Faculty of Engineering, Baze University, Abuja, Nigeria
[2]Department of Civil Engineering, Faculty of Engineering, Baze University, Abuja, Nigeria
[3]Interdisciplinary Research Center for Membrane and Water Security, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia
*Corresponding author. Email: abdullahi.sada@bazeuniversity.edu.ng

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Abstract

Electricity management and power sources must be properly managed to ensure efficient usage of electricity. This necessitates the requirement for accurate electrical demand forecasting to ensure that electricity generation is sufficient to meet demand. This paper investigates two methods of adaptive neuro-fuzzy inference systems (ANFIS), grid partitioning (GP) and subtractive clustering (SC), in predicting the load demand of Abuja City. The input parameters used for modelling are wind speed, solar radiation and air temperature. The performance of the two models - ANFIS-GP and ANFIS-SC - are compared using determination coefficient (R^2) and mean absolute percentage error (MAPE). The results showed that ANFIS-SC outperformed ANFIS-GP with a better goodness-of-fit (R^2) of 93.21% and lesser error result (MAPE) of 8.99% which proves it can be used for load demand forecasting.

Keywords: Adaptive neuro-fuzzy inference system; Grid partitioning; Load demand forecasting; Subtractive clustering

1. Introduction

The development of every country is tied to reliability, efficiency, dependability and accessibility of electric energy as it directly affects the industrial sector, health sector, population, education and quality of life as a whole [1]. Because energy is a critical input to the country's industrial sector, energy demand rises in tandem with industrial function growth. Rapid developments in business and the economy have a significant impact on energy use [2], [3]. As a result, energy consumption is a significant economic measure that indicates a city's or country's economic progress [4].

Consequently, electricity management and power sources must be properly managed to ensure efficient usage of electricity [5], [6]. High-quality capacity planning, scheduling, and operation of electric power systems are critical to this. Electricity production, transmission, distribution, and consumption all take place at the same time. This necessitates the requirement for accurate electrical demand forecasting to ensure that electricity generation is sufficient to meet demand. However, forecasting energy demand is difficult because demand series can contain unanticipated trends, high noise levels, and exogenous variables [7]. Despite the difficulty of implementing demand forecasting, the need of projecting power usage has been a hotly debated topic in recent years. This has resulted in the creation of several new forecasting tools and approaches; yet, a more accurate forecasting tool is still required.

Over the years, numerous forecasting tools have been used by researchers [8]–[10]. One of which is the Adaptive Neuro-Fuzzy Inference System (ANFIS). For instance, [11] used a technique which integrates one step-ahead concept into ANFIS to develop a model that enhances electricity load prediction by adaptive forecasting equation. Another study used a neuro fuzzy modelling technique for developing prediction models for performance and emission parameter of a dual fuel engine [12]. Genetic algorithm was further used to optimize the ANFIS model. [13] Proposed a unified method comprising of Hilbert-Huang Transform (HHT), Regrouping Particle Swarm Optimization (RegPSO) and Adaptive Neuro-Fuzzy Inference System (ANFIS) for day-ahead prediction of electric load consumption in buildings. The predictions are further used for smart choices for distributed energy management systems. [14] Proposed and presented an ANFIS model to forecast sea surface temperature (SST) in the Cąnakkale Strait using monthly air temperature, evaporation and precipitation as input data of the model. [15] Collected earthquake data from 1906 to 2019 and used it to predict the magnitude of earthquake using ANN and ANFIS. The performance and efficiencies of the two models were compared. Due to the fact that ANFIS model varied in its performance for the learning process-based membership function. To the best knowledge of the current research, this study was designed to investigate the capability of ANFIS which is a multi-layer FFNN model that characterizes an input space to an output space using ANN learning algorithms and fuzzy reasoning [16]. Considering that most research are adopted to basic ANFIS model development, this research aims analyze the two existing forms of ANFIS, that is, Grid Partitioning (GP) and Sub Clustering (SC), for load demand forecasting.

2. Study Area

Nigeria is located between the equator's latitudes 4N and 14N, and the green meridian's latitudes 2E and 15E. Nigeria is bordered on the east by Cameroon and Chad, on the west by the Benin Republic, on the north by Niger, and on the south by the Gulf of Guinea. The overall land area of the nation is 925, 796 km^2. Nigeria's key location in West Africa and Africa as a whole provides the country with a diverse spectrum of climatic changes from north to south. Our study area Abuja(see Figure 1), the Federal Capital Territory of Nigeria is located between latitude 8.25 and 9.20 north of the equator and longitude 6.45 and 7.39 east of Greenwich Meridian. It is referred to as the middle belt of Nigeria as it is situated in the center of the country. To its north and west, it is bordered by Niger State, its northeast by Kaduna State, east and south by Nasarawa State, and southwest by Kogi State. This study will consider the electricity demand in Abuja by a method of enhanced load prediction using artificial intelligence.

3. Methodology

In this study, two methods of ANFIS, grid partitioning and subtractive clustering, were proposed for prediction of daily electrical load. The input data set were categorized into two partitions of 75% and 25%. The former was used for calibration and the later for validation. The parameters used as input were the hourly wind speed, solar radiation and temperature for one whole day. The data was obtained from the Transmission Company of Nigeria. The organization is the intermediary between the Nigerian GENCOs and DISCOs. It receives the power generated by the GENCOs and transmits it to the DISCOs for distribution. It also ensures that the infrastructure is available for power transmission across the nation.

3.1 Adaptive neuro-fuzzy inference system

ANFIS is a combination of two machine learning techniques (neural network and fuzzy logic) into a single technique [17]. Takagi and Sugeno proposed two if-then sets of rules for the first order to

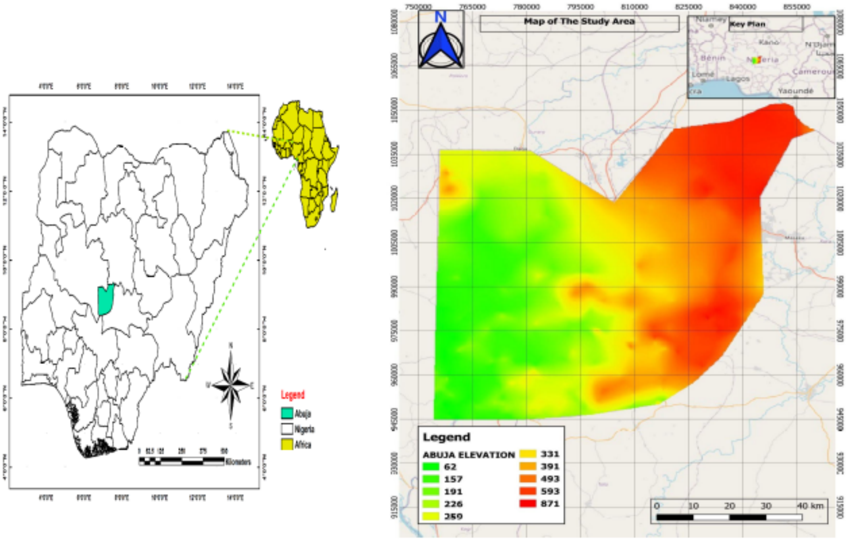

Figure 1: *Sample location of Abuja on the Nigerian map.*

describe the neuro-fuzzy [16].

Rule$_1$: If x is A_1 and y is B_1, then

$$f_1 = p_1x + q_1y + r_1 \tag{1}$$

Rule$_2$: If x is A_2 and y is B_2, then

$$f_2 = p_2x + q_2y + r_2 \tag{2}$$

where A_i and B_i are the fuzzy sets, x and y form the imput sets, f are the outputs, and p_i, q_i, and r_i are the designed parameter determine during training.

The structure of ANFIS consists of five distinct layers as depicted in Figure 2. Layer one is refer to as fuzzification layer which is described by Eq. (3) and Eq. (4).

$$\mu A_i(x) = gbellmf(x; a, b, c) = \frac{1}{1 + |\frac{x-c}{a}|^{2a}} \tag{3}$$

$$O_i^1 = \mu A_i(x) \tag{4}$$

Layers two and three describe the rule layer provided by Eq. (5) as computed by layer one, as well as the normalization of each rule using Eq. (6) [18].

$$O_i^2 = w_i = \mu A_i(x)\mu B_i(y), \quad i = 1, 2 \tag{5}$$

$$O_i^3 = \frac{w_i}{w_1 + w_2 + w_3 + w_4}, \quad i \in \{1, 2, 3, 4\} \tag{6}$$

Layer four represents the defuzzification process in each node using Eq. (7), whereas layer five provides the actual summation of ANFIS by adding the output for each rule in defuzzification layer Eq. (8).

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_ix + q_iy + r_i) \tag{7}$$

where $\overline{w}_i$ is the output of normalization from Eq. (6).

$$O_i^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{8}$$

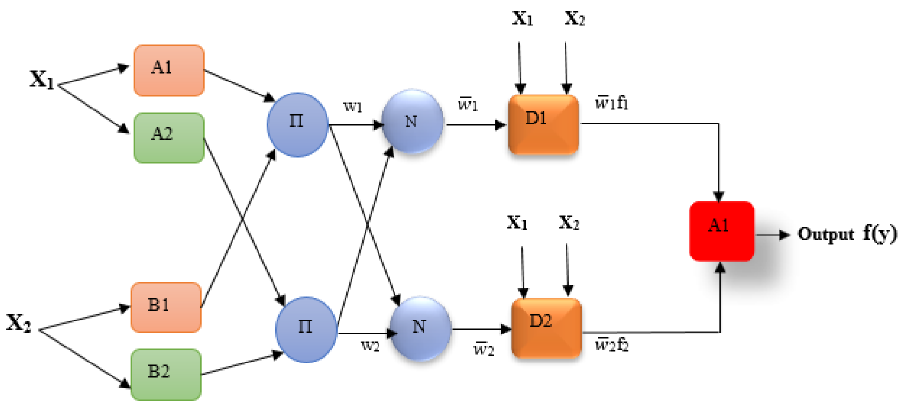

Figure 2: *Structure of ANFIS.*

3.2 Grid partitioning

ANFIS Grid Partition (ANFIS-GP) model was created by merging ANFIS and grid partition. Grid partition divides the input space into rectangular subspaces by axis-parallel partition based on a preset number of MFs and their types in each dimension. The least square method is used to calculate fuzzy sets and parameters based on partition and MF type [19].

3.3 Subtractive clustering

The ANFIS subtractive clustering (ANFIS-SC) model was created by combining ANFIS with subtractive clustering. This model is an extension of [20] mountain clustering method, in which each data point (rather than a grid point) is taken as a center for prospective cluster centers [21]. With this technique, the number of effective "grid points" to be assessed equals the number of data points, regardless of the problem's dimension. Another advantage of this strategy is that it eliminates the need to specify a grid resolution, which requires consideration of tradeoffs between accuracy and computational complexity. The subtractive clustering approach further broadens the mountain method's criterion for admitting and discarding cluster centers.

3.4 Performance Criteria

MAPE and R^2 performance evaluation criteria were employed to assess the effectiveness of these models. MAPE is a well-known measure that is commonly utilized in time series prediction. MAPE is a well-known measure that is commonly utilized in time series prediction [22], [23]. R2 has a range from 0 to 1. And the higher the value of R^2, the better the model's performance. A complete evaluation of the model's generalization performance [16] may be created by using many criteria [24], [25]. The equations for MAPE and are shown in (9) and (10) below;

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \widehat{y}_i}{y_i}\right| \times 100\% \tag{9}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \widehat{y}_i)^2}{\sum_{i=1}^{N}(y_i - y_{mean})^2} \tag{10}$$

where y_i is the observed load demand, $\widehat{y}_i$ is the predicted load demand, y_{mean} is the mean of y, and N is the size of the testing set.

4. Results and Discussion

The main objective of this study is to forecast load demand of Abuja using two methods, ANFIS-GP and ANFIS-SC and compare their performances. The simulation was done using the interface of MATLAB 2021a. The model simulations were evaluated with the most exploited performance criteria, R^2 and MAPE in both calibration and verification. Based on the models simulated, the results of the performance criteria are presented in Table 1.

The constructed model was used to generate surface plots that demonstrate the relationships between the governing design factors. The impact of each individual parameter on performance was therefore more precisely dissected. Hence, Figure 3 below illustrates the effect of different input combinations on load demand.

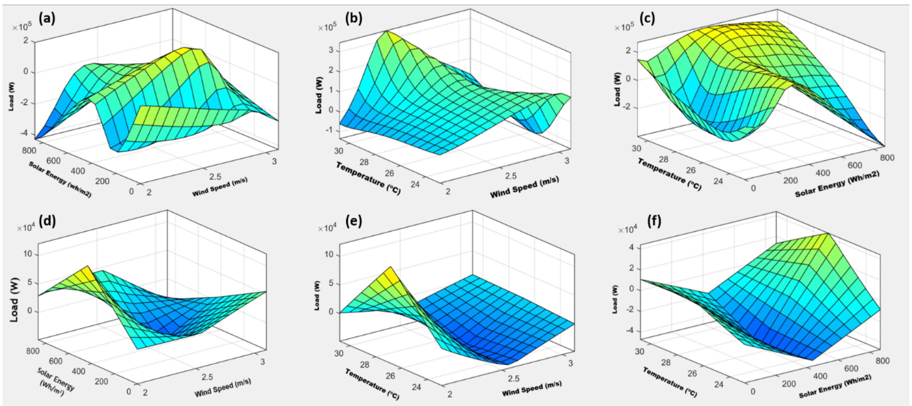

Figure 3: *Surface plots (a) (b) (c) ANFIS-SC (d) (e) (f) ANFIS-GP.*

ANFIS-GP. On the MATLAB ANFIS interface, the number of input membership functions (mf) selected were 3, the type of mf selected was triangular mf (trimf), the output mf type was constant, an error tolerance of 0.005 was used and epoch of 50 was also selected.

ANFIS-SC. For the subtractive clustering method, a range of influence of 0.5 was selected, squash factor of 1.25, accept ratio of 0.5, reject ratio of 0.15, error tolerance of 0.005 and epoch of 50 was also selected.

Performance Results. Holdout cross validation was employed and 75% of the data was used for training while 25% was used for testing. Table 1 shows the values of R^2 and MAPE that were calculated for the testing and training phase of each method.

Table 1: *R^2 and MAPE values for ANFIS-GP and ANFIS-SC.*

	R^2-Training	R^2-Testing	MAPE-Training	MAPE-Testing
ANFIS - GP	0.9429	0.7903	5.6661	8.9933
ANFIS - SC	0.9439	0.9321	6.1716	5.5789

From the two methods employed, ANFIS-SC outperformed ANFIS-GP with a better goodness-of-fit (R^2) of 93.21% and lesser error result of 8.99%. The time series and scatter plots of the two methods were also plotted and displayed in Figures 4 and 5 below. From the time series plot, ANFIS-SC also shows a better fit. Especially at the later hours of the day.

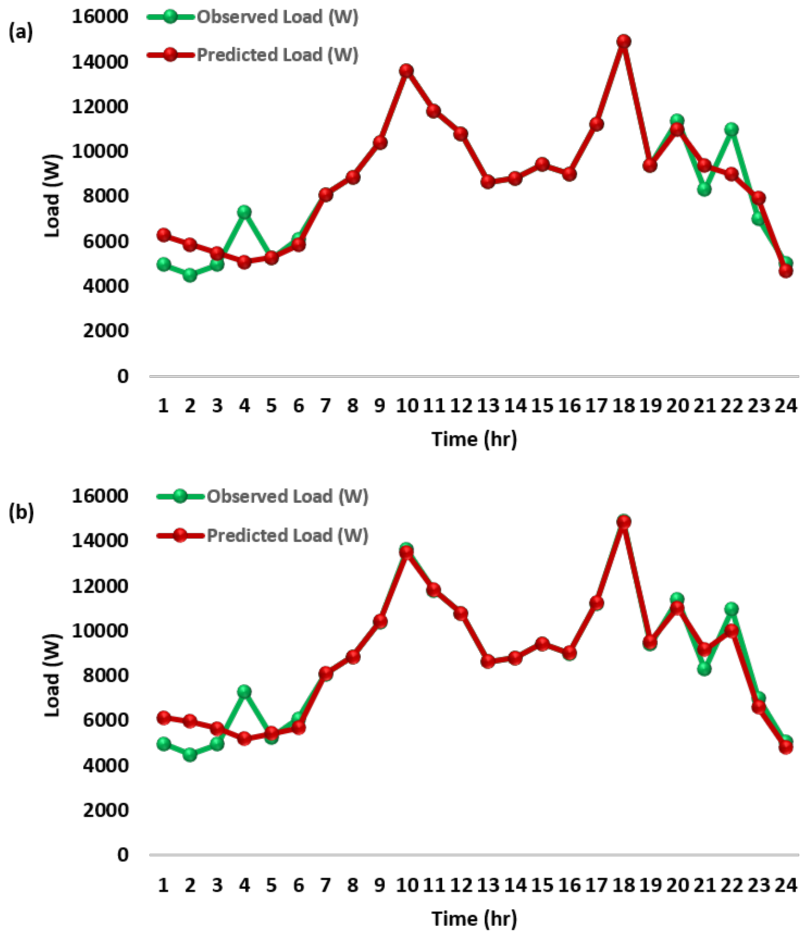

Figure 4: *Time series plot (a) ANFIS-GP (b) ANFIS-SC.*

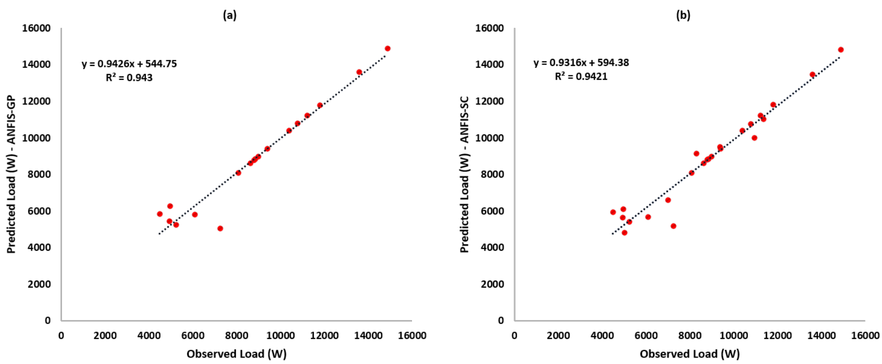

Figure 5: *Scatter plots (a) ANFIS-GP (b) ANFIS-SC.*

5. Conclusion

The need for proper management of electricity and power sources to ensure efficient usage of electricity necessitates the requirement for accurate electrical demand forecasting. This paper presents two methods of adaptive neuro-fuzzy inference systems (ANFIS), grid partitioning (GP) and subtractive clustering (SC), in load demand forecasting for Abuja City. The performance and efficiency of the models employed were evaluated using R2 and MAPE. The results obtained from this work revealed that ANFIS-SC performed better than ANFIS-GP in forecasting load demand of Abuja City with R^2 values of 94.39% and 93.21% and MAPE values of 6.1716 and 5.5789 in training and testing phase respectively. Because of this, ANFIS-SC proves to be a promising model for load demand forecasting. However, further optimization methods can be applied to improve the accuracy of the model.

Conflicts of Interest: **The authors have no conflict of interest to any part.**

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