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Research Article

Optimization of ANFIS Model for Improved Short-term Electrical Load Forecasting

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Abstract

For power systems to be stable and reliable, an accurate prediction of electrical load demand is crucial. Electric utilities rely on short-term load forecasting to effectively manage the generation, transmission, and distribution of power to satisfy customer demand. Artificial Neuro-Fuzzy Inference System (ANFIS) is utilized in this work for short-term load forecasting due to its propensity to manage non-linear relationships and uncertainty. ANFIS method has been used in the past for short-term load forecasting, there are certain conditions and issues that need to be resolved. Data normalization, choice of optimization technique, and choice of membership function can greatly influence short-term load forecast using ANFIS. Thus, this paper explored the different choices available and recommended the best choices based on the results obtained. Hourly electrical load data from 24th November 2021 to 4th January 2022, sourced from University of Lagos Power Station, and relevant temperature data within the same range sourced from National Solar Irradiation Database (NSRDB) were used to train and test the various ANFIS architectures. Different ANFIS models, including different membership functions and sets of input data, were simulated on MATLAB, and the performance of the models was evaluated using standard matrices such as root mean square error (RMSE) and mean absolute percentage error (MAPE). The result of this study showed that the inclusion of temperature as an exogenous variable and the use of Gaussian membership function yielded a higher forecast accuracy with MAPE 0.05754% and RMSE 0.56614. This implies that using temperature as an input variable and Gaussian membership functions can improve forecasting accuracy.

Keywords

Short-term Load Forecasting, Artificial Neuro-Fuzzy Inference System (ANFIS), Artificial Intelligence

1. Introduction

Electrical load forecasting is of paramount importance for electricity providers as it allows them to effectively plan the generation and distribution of electricity to meet customer demands. Load forecasting involves intelligently predicting load demand trends to determine future growth with reliability and precision [1, 2]. The main objective of load forecasting is to accurately predict future load patterns in a specific area or region using past electrical load data from the said area. It is crucial for electricity utilities and grid operators to forecast load accurately in order to make sure there is enough capacity to meet the demand for power [3, 4]. If the system load forecast is overstated, the system may overcommit the generation

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of energy, which may unintentionally result in expensive operation of the power system. On the other side, if the system load projection is understated, the system's dependability and security may be jeopardized, leading to power outages and unhappy customers [5]. Load forecasting is classified by the time period during which the forecast was carried out. Short-term load forecasting (STLF) predicts the electrical load for a period ranging from a few hours to a few days. Medium-term load forecasting (MTLF) involves forecasting the load for a duration of a few weeks to several months. On the other hand, long-term load forecasting (LTLF) focuses on predicting the load for timeframes longer than one year [6].

Short-term forecasting holds significant importance in improving a country's energy system, notably in terms of operating and controlling power generation and distribution by determining the work schedule of power plants and selecting the right production group [3, 7]. Energy companies deal with a wide range of operational, planning, and technological concerns linked to electricity regulation and management [1]. Short-term forecasting enables utilities and grid operators to predict and respond to hourly or daily fluctuations in electricity demand [8]. Utilities and grid operators can ensure that the electricity system remains stable and that there is enough generation capacity to fulfill predicted demand by accurately estimating short-term demand [9, 10].

The global demand for reliable forecasting models has intensified, affecting both rural and urban areas in various countries [11]. Many statistical and Artificial intelligence models have been proposed for load forecasting [2, 12]. These techniques utilize historical electrical load data, along with additional variables like weather data, to predict future values of the electrical load. Some of the statistical methods used in the past include autoregressive integrated moving average (ARIMA) models, exponential smoothing, and regression analysis [13, 14]. The advantage of statistical approaches is that they use straightforward prediction [15]. However, the relationships between load and the variables affecting it are not linear; therefore, it is difficult to model this nonlinearity using statistical methods [16]. The use of artificial intelligence for electrical demand forecasting has recently attracted significant attention and initiatives. This is due to its ability to learn and model nonlinear and complex relationships between loads and the variables affecting it [17, 18]. Artificial neural networks (ANN) are particularly well-suited for load forecasting because they can handle a large amount of data and can learn and adapt to changing patterns in the data over time [19], however, ANN may be less effective at handling uncertain and imprecise data and may require a larger amount of data to be effective [20]. Artificial Neuro-Fuzzy Inference System (ANFIS) is a hybrid method that combines the strengths of both fuzzy logic and ANN [21]. ANFIS has the capability to learn from historical data and make predictions based on that acquired knowledge; therefore, it is a well-suited approach for short-term electrical load forecasting [22, 23].

There is a non-linear relationship between electrical load and exogenous factors affecting it, which can significantly impact the accuracy of short-term load forecasting [24]. Factors that affect electrical load forecasting include: time factors, weather factors, economic factors, and random disturbances [25].

Time Factors: The structure of the load pattern behaves differently across different time periods. These time periods include: hour of day, day of week, public and religious holidays, and seasonal changes. Electricity usage varies significantly between workdays and holidays, whilst noting that the load demand pattern is different for different days. Due to their proximity to the weekend, Mondays and Fridays, for instance, could have structurally different loads than Tuesday through Thursday [26]. Load demand during vacations is more difficult to estimate due to their infrequency [27].

Weather Factor: Weather is one of the factors that contributes to significant variations in load demand patterns. This is due to the fact that the majority of utilities have significant load components that are weather-sensitive. An important variable in the weather factor is temperature. A deviation in temperature from its expected value might create a significant shift in the load demand pattern. For short-term load forecasting, the weather component must be taken into account [28].

Economic Factors: Economic factors affect majorly long-term load forecasting, however it also affects short-term load forecasting. The daily load curves of developed and developing countries, for example, differ because maximum consumption differs for both parties. Electricity costs also have an impact on load demand patterns, as high electricity prices lead home customers to use less power [25].

Some studies found that the inclusion of exogenous variables, such as weather patterns (temperature) and economic conditions, improved the accuracy of the forecasts, while others found that these variables had little impact [29, 30]. Sowinski [31], presented a study on the impact of exogenous variables on the accuracy of daily load forecasting. The author finds that the inclusion of certain exogenous variables, such as temperature and humidity, can significantly improve the accuracy of the forecasts, while the inclusion of other variables has a lesser impact or no impact at all. Bozkurt et al. [32], considered the use of various exogenous factors, including historical load data, electricity prices, day type, weather conditions, and exchange rates, for short-term load forecasting. The findings indicated that the utilization of calendar data and historical load data as inputs yielded the most accurate forecasts. Weyermüller et al. [33], observed that incorporating public holidays in short-term load forecasting potentially enhanced the overall forecast accuracy. Further research is needed to fully understand the conditions under which these approaches are most effective.

Though ANFIS method has been used in the past for short-term load forecasting, there are certain conditions and issues that need to be resolved. Data normalization, choice of optimization technique, and choice of membership function can greatly influence short-term load forecast using ANFIS. Thus, this paper explored the different choices available and recommended the best choices based on the results obtained.

2. Materials and Methods

2.1. Artificial Neuro-Fuzzy Inference System (ANFIS)

Roger Jang created the ANFIS method to address the drawbacks of ANNs and fuzzy systems [34]. ANFIS integrates the principles of fuzzy logic and neural networks, allowing it to harness the benefits of both approaches within a unified framework [35]. ANFIS consists of a series of interconnected layers of nodes, called fuzzy rules, which use fuzzy logic to make decisions. Each fuzzy rule consists of a premise part, which specifies the input conditions, and a consequence part, which specifies the output action. The fuzzy rule in ANFIS consists of a set of fuzzy sets representing the input variables in the premise part, while the consequence part involves a defuzzification process that transforms the fuzzy output into a precise value. ANFIS provides faster results than ANN in the short-term load forecasting process [26]. Figure 1 shows ANFIS architecture with an output and two inputs.

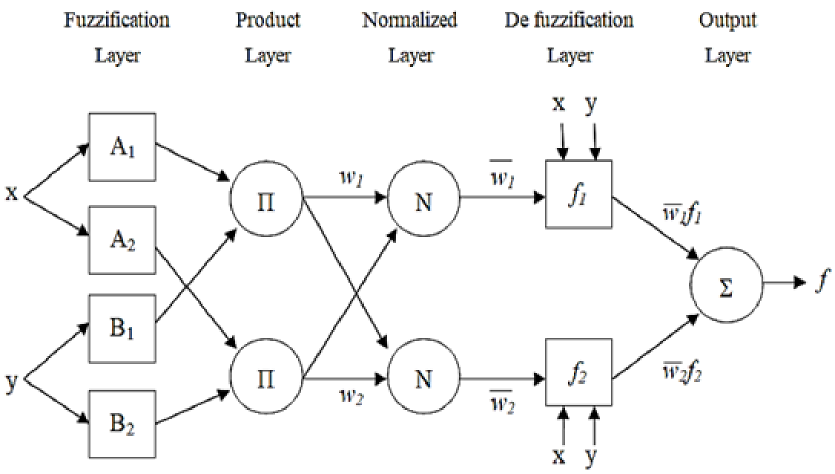

Figure 1. *ANFIS Architecture with two inputs and an output.*

The steps applied in the Fuzzy Inference System model include: Fuzzification, rule evaluation, defuzzification, and output membership function.

Fuzzification: (Layer 1) is the process of mapping the input data to fuzzy sets using membership functions.

$$\mu_{A_i}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \tag{1}$$

Where A_i and B_i are membership functions, (a_i, b_i, c_i) are parameter set.

Rule Evaluation/ Inference: (Layer 2 and 3) Involves using the fuzzy rules to make a prediction based on the input data. The output of this layer is the multiplication of the incoming values.

$$O_{2,I} = w_i = \mu_{A_i}(x) \times \mu_{Bi_i}(x) \tag{2}$$

Where i = 1, 2.

Defuzzification: (Layer 4) involves the conversion of the fuzzy output into a precise or crisp value.

$$O_{3,1} = \overline{w_i} = \frac{w_i}{w_1+w_2} \tag{3}$$

The output membership function is weighted and summed, which gives the output of the forecasted load.

$$O_{4,1} = \overline{w_i}f_i \tag{4}$$

$$O_{5,i} = \sum_i \overline{w_i}f_i \tag{5}$$

Several research studies have established that ANFIS outperforms other models in short-term load forecasting [22, 36, 37]. ANFIS is capable of handling data uncertainty and imprecision, which are commonly encountered in load forecasting due to external factors like weather and economic conditions [22]. The training of the Neuro-Fuzzy Model involves utilizing historical data, specifically the hourly electrical load data supplied to the University of Lagos Power Station from 24th November 2021 to 4th January 2022. The model was trained using data obtained from 24th Nov 2021 to Jan 4, 2022. Then the model was tested using the data obtained from Dec 22 to 28, 2022. Exogenous variables such as temperature were sourced from National Solar Irradiation Database (NSRDB). Figure 2 shows the Flowchart for training of the proposed ANFIS forecasting models. The ANFIS system involves 4 essential steps: Data preprocessing, Fuzzy inference system generation and optimization, training and testing, and finally the result.

2.2. Data Preprocessing

The data preparatory steps include data cleaning and Normalization. Microsoft Excel was used to clean the input data to verify that it is accurate, with missing or invalid values handled appropriately. The input data was then split into three sections for training, validating, and testing, respectively. Normalization is a process of scaling input data to a common range, which can help improve the performance of ANFIS and other machine learning models. Normalization is done because the activation function of the neural network operates in an optically small range. *A Min-Max normalization technique is utilized in this work*. In this technique, data is scaled such that they are within the range (0,1) using equation (6).

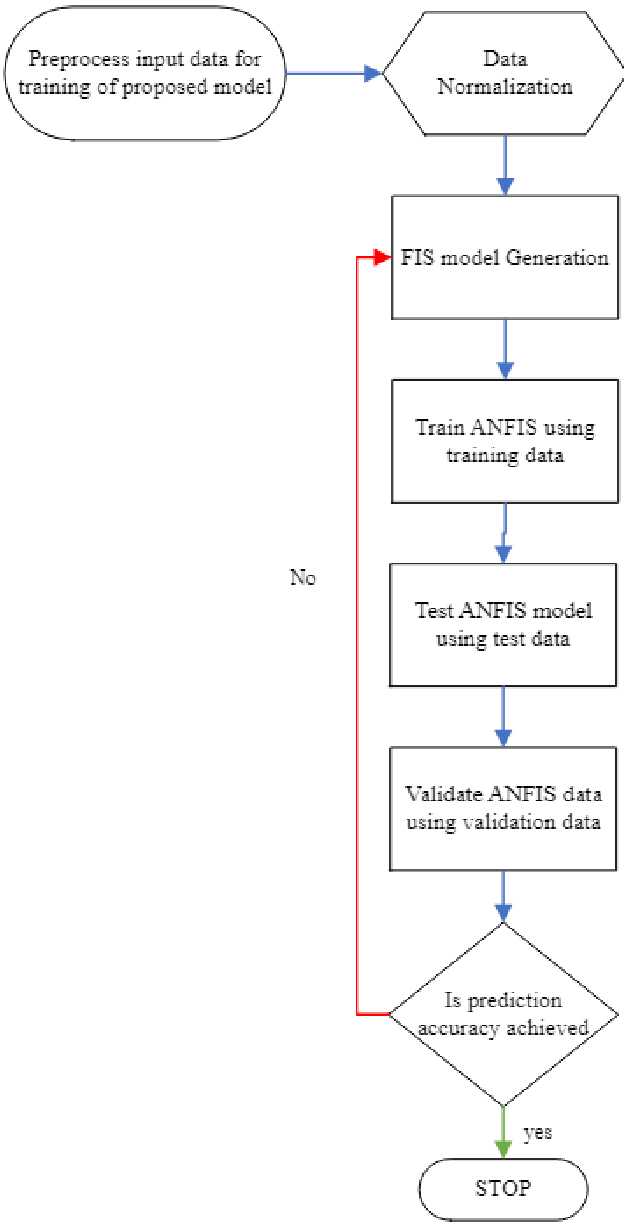

Figure 2. *Flowchart for training of proposed models.*

$$L_s = \frac{L_A - L_{min}}{L_{max} - L_{min}} \tag{6}$$

Where,

L_s = normalized or scaled load
L_A = actual load
L_{min} = minimum load
L_{max} = maximum load

2.3. ANFIS Model Architecture

The selection of input parameters significantly influences the performance of the ANFIS model for short-term load forecasting [33, 38]. Selecting the most relevant input variables decreases the number of input parameters, enhancing ANFIS model efficiency and accuracy since the number and variety of input parameters affect ANFIS model training complexity and time [39]. In this work, two ANFIS models are proposed. One in which the model is trained considering an exogenous variable (temperature was considered), and another in which the exogenous variable was ignored. Neuro-Fuzzy Designer Apps from MATLAB R2019b were used for load forecasting in this work. Figure 3 shows the ANFIS structure with 3 inputs (hour of day, previous load demand, and temperature), while Figure 4 shows the ANFIS structure with 2 inputs (hour of day and previous load demand).

The membership functions determine the shape of the fuzzy set and how the membership values are assigned. The selection of the membership function is crucial as it determines how the input data is mapped to the fuzzy sets and how these sets are combined to generate the final output. Hence, the choice of the membership function holds significance in the overall process. *Some membership functions that can be used in ANFIS model include triangular, trapezoidal, generalised bell, and Gaussian functions. In this work, the Gaussian and generalised bell membership functions were used in the different ANFIS models and the most effective will be determined from the results.* The number of membership functions starts with a small number and gradually increases if there is a need to improve the model performance. Table 1 shows the specifications used for training each ANFIS model.

Table 1. *Specification of Proposed ANFIS Model.*

Membership function	**No of membership function**	**No of Epoch**	**Input**	**Training Error**	**Average Testing error**
Gaussian	3,3,4	60	Hour of the day, Temperature, Previous hour load demand	0.054336	0.56614
Gaussian	3,4	60	Hour of the day, Previous hour load demand	0.079511	0.04101
Generalized Bell	3,3,4	60	Hour of the day, Temperature, Previous hour load demand	0.055509	0.21808
Generalized Bell	3,4	60	Hour of the day, Previous hour load demand	0.080036	0.042776

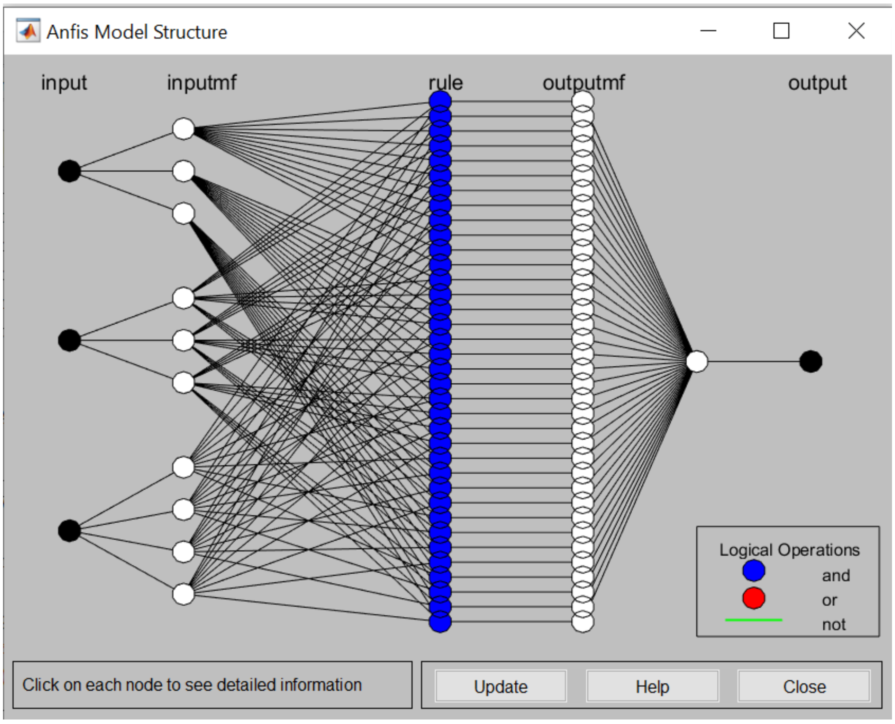

Figure 3. *ANFIS Structure With 3 Input Layers And 3 3 4 Membership Function.*

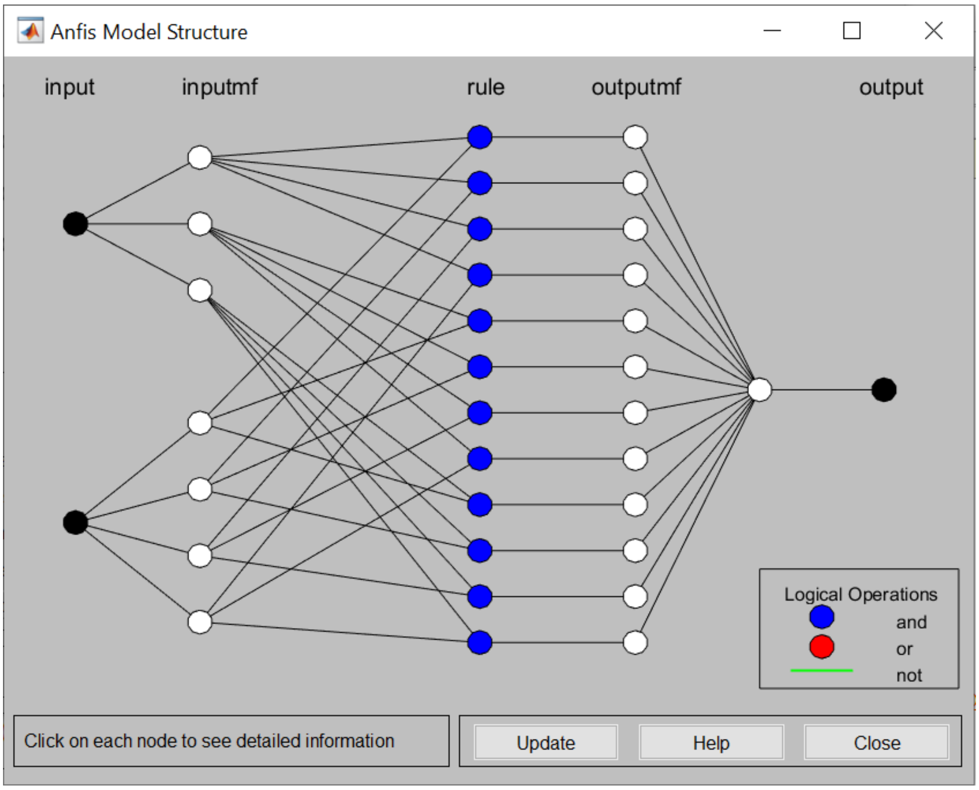

Figure 4. ANFIS Structure With 2 Input Layers And 3 4 Membership Function.

2.4. Training, Optimization and Testing of ANFIS Model

The ANFIS training algorithm's main objective is to minimize the approximation error. The model is fed with the first section of input data (training data) for training of the ANFIS. The training algorithm data required include: optimization technique, error tolerance, and number of training epochs. The optimization technique tunes the FIS model parameters and hence improves the accuracy of the model. These techniques function by modifying the weights and biases of the FIS model to reduce the error between the predicted output and the actual output, aiming to minimize the error. The hybrid optimization technique is chosen for this work, which combines the gradient descent back propagation and least mean square optimization algorithms.

The number of training epochs refers to how many times the model will iterate through the training data during the learning process. The number of training epochs should be sufficient to improve model accuracy and avoid overfitting. At each epoch, the error measure is reduced. Training ends when a predefined number of epochs or the error rate is reached. After the model is trained, a separate portion of the input data, known as the testing data, is employed to evaluate the model's performance. This step aims to assess the model's ability to generalize to new data without overfitting to the training data.

2.5. Performance Evaluation

The accuracy of the model is measured using mean absolute percentage error (MAPE) and root mean square error (RMSE).

$$MAPE = \frac{1}{n}\sum_{j}^{n}\left|\frac{A_i - F_i}{A_i}\right| \times 100\% \quad (7)$$

Where,
$n =$ Total number of data points
$A_i = actual\ \ value$
$F_i = forecasted\ \ value$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(F-A)^2}{n}} \quad (8)$$

Where,
$n = Number\ \ of\ \ samples$
$F = Forecast\ \ value$
$A = Actual\ \ value$

Lower MAPE and RMSE indicate the best ANFIS model for short-term load forecasting.

3. Results and Discussion

The following results, which show the comparison between the actual load and the predicted load, were obtained during the simulation. Table 2 shows the results obtained from each ANFIS model using the validation data (Wednesday, 22nd, 2022) for 60 epochs of training. Figures 5 and 6 show the plots of actual load and predicted load by the different ANFIS models using the validation data (22nd December to 28th December, 2022).

Table 2. *Result Obtained for Wednesday 22nd, December 2022.*

Time (Hour)	Actual Demand	Predicted Load Demand (MW) Gaussian (No temperature)	Gaussian (With temperature)	Generalized bell (With Temperature)	Generalized bell (No temperature)
0	0.1901	0.193853253	0.18399742	0.183997	0.1819
1	0.1795	0.186580561	0.17318745	0.173187	0.1697
2	0.1715	0.177925093	0.16479462	0.164795	0.1669
3	0.1642	0.172624272	0.16590908	0.165909	0.1688
4	0.1622	0.164719118	0.17263393	0.172634	0.1745
5	0.2052	0.170198372	0.09554178	0.095542	0.1606
6	0.2829	0.229729261	0.21811452	0.218115	0.234
7	0.3178	0.347315273	0.31803409	0.318034	0.3091
8	0.3626	0.388065952	0.37944162	0.379442	0.3877
9	0.4070	0.439584603	0.4526625	0.452663	0.4572
10	0.5104	0.480358751	0.49776024	0.49776	0.4971
11	0.5166	0.530120607	0.52179047	0.52179	0.5283
12	0.4964	0.528422254	0.5018063	0.501806	0.4958
13	0.4763	0.493998242	0.47688203	0.476882	0.493
14	0.3718	0.455410984	0.46062583	0.460626	0.4846
15	0.3944	0.359091114	0.38599388	0.385994	0.3869
16	0.3369	0.375470032	0.36752281	0.367523	0.3695
17	0.3340	0.331701938	0.32722003	0.32722	0.3277
18	0.3289	0.328466942	0.34668149	0.346681	0.3448
19	0.3053	0.319004379	0.34067704	0.340677	0.3444
20	0.2994	0.289255126	0.30773516	0.307735	0.3148
21	0.2758	0.278276272	0.28746318	0.287463	0.2924
22	0.2658	0.253127219	0.25749106	0.257491	0.2588
23	0.2037	0.243624875	0.23612053	0.236121	0.2347

Table 3 shows the result of the training performance index; Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

Table 3. *Results of the training performance index.*

Membership function	Input	MAPE	RMSE
Gaussian	Hour of the day, Temperature, Previous hour load demand	0.05754	0.56614

Membership function	Input	MAPE	RMSE
Gaussian	Hour of the day, Previous hour load demand	0.07835	0.04101
Generalized Bell	Hour of the day, Temperature, Previous hour load demand	0.07693	0.21808
generalized Bell	Hour of the day, Previous hour load demand	0.0975	0.042776

The results indicate the significance of including temperature as an input and the impact of different membership functions on the model's accuracy.

When temperature was included as an input, the ANFIS model with Gaussian membership function achieved a MAPE of 0.05754 and an RMSE of 0.56614. On the other hand, the model with the generalized bell membership function yielded a slightly higher MAPE of 0.07693 and a lower RMSE of 0.21808. These findings suggest that both membership functions contributed to accurate load forecasting, with the Gaussian function outperforming the generalized bell function.

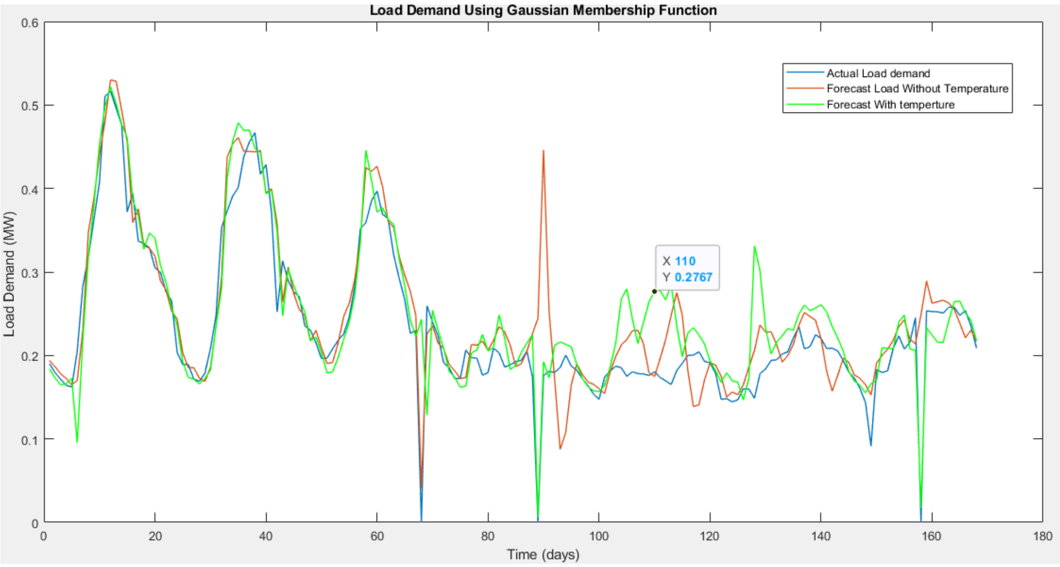

__Figure 5.__ Plot of Actual Load demand & Forecasted demand Using generalized Bell Membership Function (22nd December to 28th December, 2022).

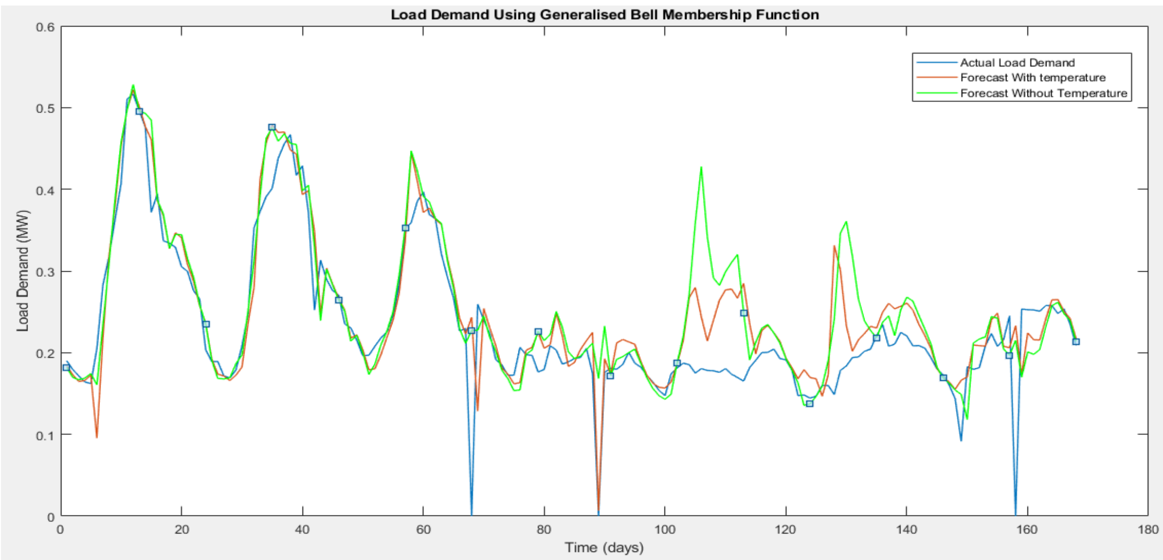

__Figure 6.__ Plot of Actual Load demand & Forecasted demand Using Gaussian Membership Function (22nd December to 28th December, 2022).

When temperature was not included as an input, the ANFIS model with Gaussian membership function achieved a higher MAPE of 0.07835 and a lower RMSE of 0.04101 compared to the model with the generalized bell membership function, which had a higher MAPE of 0.0975 and a slightly higher RMSE of 0.042776. These results indicate that the inclusion of temperature as an input variable improved the load forecasting accuracy in both membership function scenarios.

4. Conclusions

In conclusion, this study successfully achieved its objectives related to investigating the optimization of Adaptive Neuro-Fuzzy Inference System (ANFIS) for short-term electrical load forecasting. The results obtained showed that the inclusion of temperature as an input variable enhances the model's predictive capabilities and emphasizes the need for selecting appropriate input variables. The study also suggests further optimization possibilities by exploring alternative membership functions and incorporating additional variables. Future research can build upon these findings to explore the use of ANFIS for short-term electrical load forecasting, considering alternative input variables, such as humidity and time of day, and investigating alternative membership functions, training algorithms, and advanced data analytics techniques. Validating ANFIS models on diverse datasets and real-world applications, incorporating uncertainty analysis, and extending their application to long-term load forecasting would also be valuable areas of future research. Future studies can also consider developing a new model to tackle similar issues.

Abbreviations

ANFIS	Artificial Neuro-Fuzzy Inference System
MAPE	Mean Absolute Percentage Error
NSRDB	National Solar Irradiation Database
LTLF	long-term Load Forecasting
MTLF	Medium-term Load Forecasting
STLF	Short-term Load Forecasting

Author Contributions

Osita Omeje: Conceptualization, Investigation, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing

Favour Edwards: Conceptualization, Formal Analysis, Investigation, Software, Visualization, Writing – original draft

Linus Idoko: Conceptualization, Data curation, Methodology, Resources, Validation, Visualization, Writing – review & editing

Data Availability Statement

The data supporting the outcome of this research work have been reported in this manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

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