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Advanced Neural Network-Based Electrical Load Demand Forecasting for Distribution Network Applications

W. Ikonwa, E. C. Obuah

[1,2] *(Electrical Department, Rivers State University, Port Harcourt, Nigeria)*

ABSTRACT

Accurate load forecasting constitutes a fundamental component of power system planning, operational optimization, stability assessment, and effective network management. In this study, Artificial Neural Networks (ANN) and an Adaptive Neuro-Fuzzy Inference System (ANFIS) were implemented within the MATLAB/Simulink environment to predict electrical load demand for the study area over a 13-year horizon (2023–2035). The forecasting framework utilized month and year as input variables, while aggregated load consumption served as the output parameter. During model training, the ANFIS achieved a minimum mean squared error (MSE) of 0.307983, converging rapidly at epoch 2. In comparison, the ANN model recorded an MSE of 0.3201 at epoch 10. The lower MSE and faster convergence rate indicate superior predictive performance of the ANFIS model for the Abuloma 33 kV distribution network. For the ANN model, the regression coefficients (R-values) obtained during training, validation, and testing phases were 0.9289, 0.9262, and 0.9501, respectively, demonstrating a strong correlation between the predicted outputs and the measured load data. Historical load data from the Abuloma 33 kV Injection Substation (2010–2022) revealed a steady increase in demand from 4.9 MW to 9.1 MW. Based on the ANFIS forecasting results, the projected load demand is expected to rise from 10.076 MW in 2023 to approximately 13.73 MW by 2035, indicating sustained growth in electricity consumption within the network.

Keywords: Artificial Neural Network (ANN), Load consumption, Load Forecasting, Optimization, Power Consumption, Substation, Stability.

1.0 INTRODUCTION

According to Eneje et al. (2020), load forecasting refers to the systematic utilization of historical electricity consumption data to generate reliable and accurate estimates of future load demand. Historically, the concept of electrical load prediction can be traced back to the industrial revolution, where preliminary forecasting practices were applied in relatively simple and localized power systems. Load forecasting involves the analytical estimation of future electricity demand based on prior load records and correlated influencing variables. These predictive processes incorporate historical consumption patterns alongside relevant exogenous parameters to improve estimation accuracy. With the increasing complexity of modern power systems and the need to maintain equilibrium between generation and demand, load forecasting has become a critical operational tool. Accurate demand prediction supports real-time generation scheduling, system stability control, and optimal resource allocation. Moreover, it enables utility operators to undertake proactive planning measures to ensure uninterrupted power supply and to prevent system instability or network collapse resulting from overloading conditions.

2.0 Literature Review on Electrical Load Forecasting

Babatunde et al. (2018) emphasize that load forecasting remains a critical function in power system operation, underpinning system reliability, operational stability, and the optimal planning and scheduling of generation resources for effective network management. Cullen (2019) observes that the need for electricity demand prediction emerged during the industrial revolution, albeit at a relatively modest scale. Prior to the early 1970s, electricity consumption levels were comparatively low and exhibited a fairly consistent annual growth rate of approximately 7.4%. This predictable trend was largely attributable to limited population growth, as well as minimal commercial and industrial expansion, which simplified demand estimation.

Mitchell et al. (2020) further note that early forecasting approaches during the industrial revolution were predominantly based on straightforward extrapolation techniques derived from historical consumption trends. According to Samuel et al. (2017), effective load forecasting contributes to reduced dispatch costs, enhanced generation utilization, and structured long-term system expansion planning. Additionally, it supports efficient operational scheduling and strategic decision-making within modern power systems.

Kucukdeniz (2020) asserts that electricity demand forecasting constitutes a vital activity for all participants within the power sector, as it directly influences operational planning and indirectly determines the profitability of generation and distribution companies. Inaccurate load predictions can lead to misguided strategic decisions, inefficient resource allocation, and significant financial losses for power producers.

Amlabu et al. (2020) highlight that long-term load forecasting is particularly critical for strategic unit commitment, maintenance scheduling of generating units, and the achievement of economic dispatch objectives. They further emphasize that forecasting outputs support transmission and distribution network design, system expansion planning, and the effective coordination of operational and maintenance activities in power stations.

Ibe (2020) classifies load forecasting based on prediction horizon into short-term, medium-term, and long-term categories, depending on the duration under consideration.

3.0 MATERIALS AND METHOD

3.1 Data used for Training

The mean yearly load consumption of Abuloma 33kV power network from 2010-2022 shown in table 1 was used for ANN and ANFIS training, testing and validation.

Contemporary electric load forecasting employs diverse analytical methodologies, broadly categorized into conventional statistical approaches and artificial intelligence–based techniques, particularly Artificial Neural Networks (ANN) (Aslan et al., 2019). Among intelligent hybrid methods, the Adaptive Neuro-Fuzzy Inference System (ANFIS) integrates the learning capability of ANN with the reasoning mechanism of Fuzzy Logic (FL). ANFIS combines neural network training algorithms with fuzzy rule-based inference to enhance predictive accuracy (Moradzadeh, 2021).

Fuzzy Logic systems operate by assigning linguistic variables—such as low, medium, or high to input parameters (e.g., temperature) based on defined membership functions (Al-Kandari et al., 2004). Properly structured fuzzy inference systems demonstrate robustness when applied with generalized conditional rules. However, many practical applications require precise numerical outputs; therefore, fuzzy inputs undergo logical processing and defuzzification to produce exact quantitative forecasts suitable for power system decision-making. Defuzzification is subsequently applied to convert fuzzy inference outputs into crisp numerical values, thereby ensuring accurate and precise quantitative results (Amit, 2010).

This study presents a comparative evaluation of Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models for long-term load forecasting of the Abuloma 33 kV distribution network. Both models are employed to predict electricity demand over a 13-year horizon (2023–2035), with performance assessed based on the minimization of mean squared error (MSE) to identify the most accurate forecasting approach.

Table 1: Mean yearly load consumption (Source: PHEDC)

Year	Load (MW)
2010	4.9
2011	5.2
2012	5.3
2013	5.5
2014	5.6
2015	5.7
2016	5.8
2017	6.0
2018	6.7
2019	7.3
2020	7.9

3.2 Flow charts for ANN and ANFIS

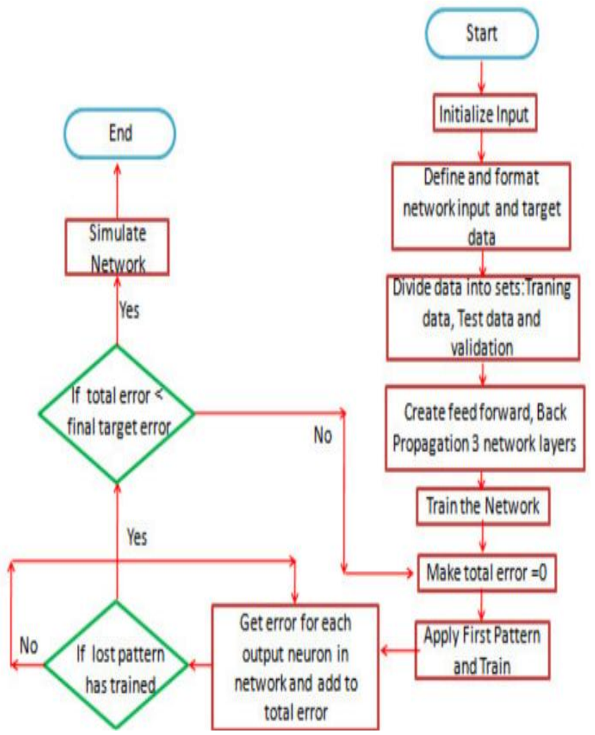

Fig. 1: Flow chart for Artificial Neural Network (Sidda et. al., 2017)

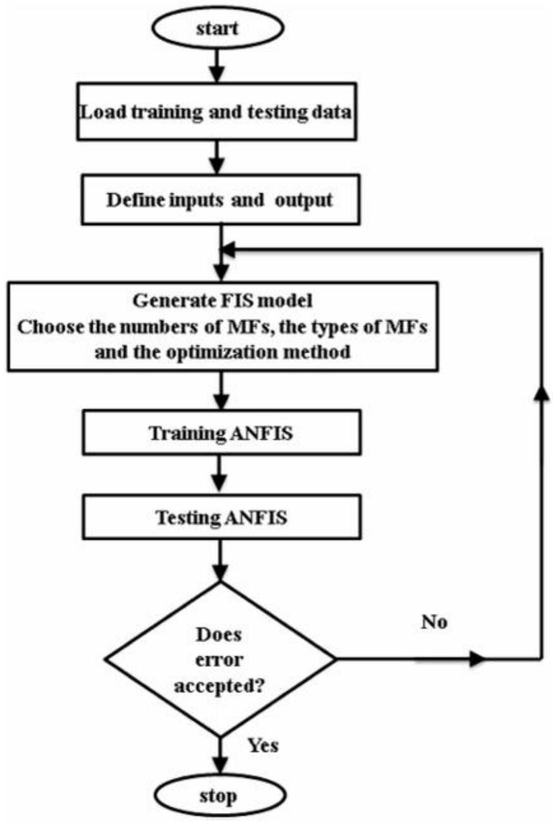

Figure 2: Flow chart for ANFIS (Omar and Hamdan, 2017)

3.3 Neural Network Modelling

The Feed Forward Backward Propagation Artificial Neural Network (FFBP-ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) tools in MATLAB/SIMULINK software were used to forecast load consumption for Abuloma area. The ANFIS uses two inputs and one output as its training set of data. Month and year are the input data, while electricity usage is the output data. The monthly and annual power consumption statistics of the Abuloma Injection Substation from 2010 to 2022 make up this training set. The Grid-Partition method was utilized to generate the Fuzzy Inference System (FIS). The Hybrid optimization method was employed to train the FIS, with 50 iterations (epochs) and a trimf type of membership function with 12 11 input membership function for the ANFIS structure. Moreover, the FFBP-ANN was used to predict the power consumption in comparison with the ANFIS. The month and year were used as the input data, and the power consumption as the target data.

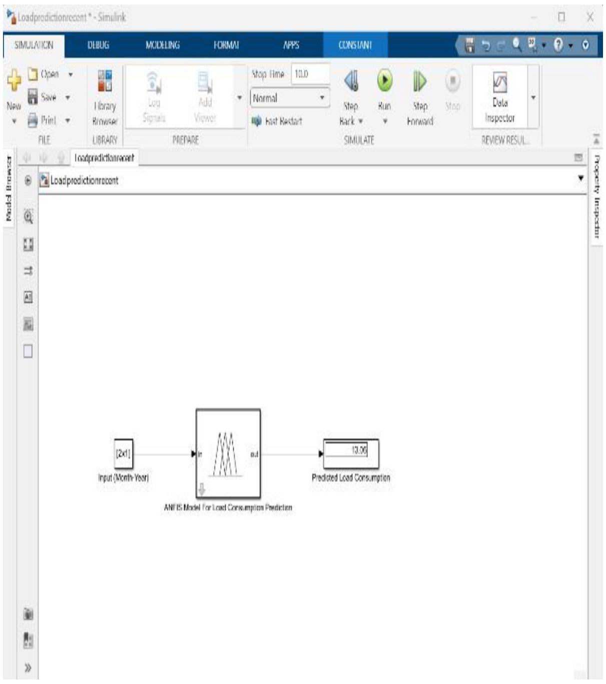

Fig. 3: ANFIS simulation Model for Predicting Power Consumption

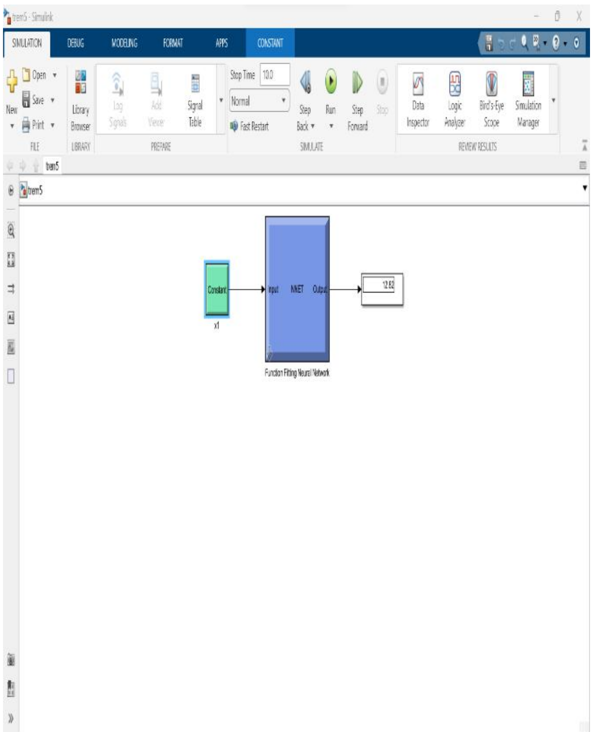

Figure 4: ANN simulation Model for Predicting Power Consumptio

4.1 Results and Discussio4.2 ANN and ANFIS Training Result

The ANFIS training was completed at Epoch 2, with a minimal mean squared error (MSE) of 0.307983.

The Levenberg-Marquardt algorithm was used to train the artificial neural network, which has a layer size of 10. The Mean Squared Error (MSE) was used to assess the neural network's performance and was found to be 0.3201. The best validation performance is 0.26902 at epoch 10. The regression results for the training, validation, and testing were 0.9289, 0.9262, and 0.9501. The outcomes of the regression analysis demonstrated that the neural network findings and the real data fit each other rather well. Table 2 displays the mean yearly power consumption forecasting simulation results for the ANFIS and ANN models based on real data.

Table 2: Mean Actual and Predicted Annual Power (MW) Consumption from 2010 – 2022

Year	Actual	ANFIS	ANN
2010	4.9	4.943	4.88
2011	5.2	5.139	5.14
2012	5.3	5.311	5.4
2013	5.5	5.472	5.62
2014	5.6	5.609	5.72
2015	5.7	5.707	5.74
2016	5.8	5.772	5.77
2017	6.0	6.009	5.99
2018	6.7	6.739	6.71
2019	7.3	7.391	7.46
2020	7.9	7.771	7.77
2021	8.1	8.137	8.11
2022	9.1	9.092	9.073

The graph in Figure 2 demonstrates how well the ANFIS and ANN models suit the actual power usage and the expected power consumption. The ANFIS model produces better and more acceptable prediction results for power consumption than the ANN model, as evidenced by the fact that its training error is less than the ANN model's. Abuloma Injection Substation's real power consumption statistics from 2010 to 2022 revealed a rise in power usage from 4.9 MW to 9.1 MW.

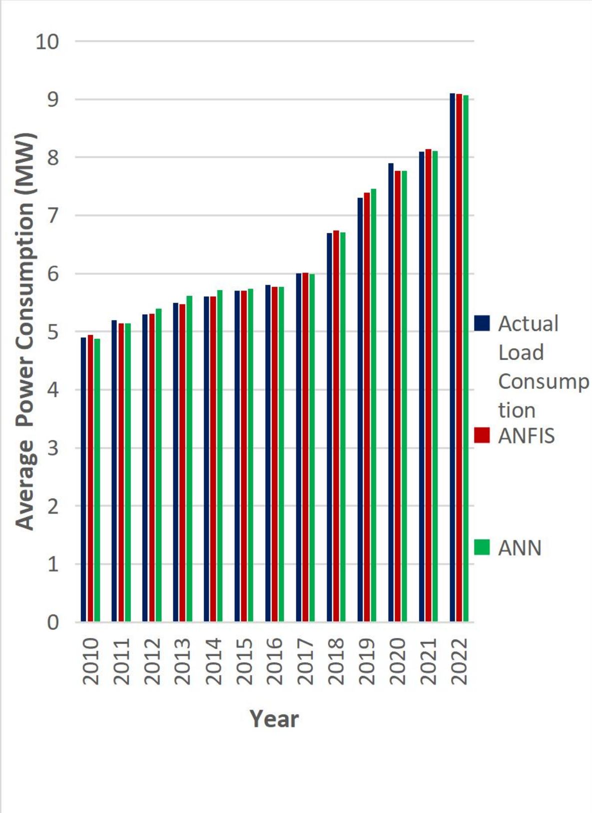

Fig. 5: Graph of Actual Power Consumption and Forecasted Power Consumption

4.3 Predicted Average Power Consumption

Tables 3 and 4 present the simulation results for the 13-year monthly power consumption of the Abuloma Injection Substation from 2023 to 2035, which was likewise predicted using the ANFIS and ANN models respectively. According to Table 3 and the graph in Figure 5, the ANFIS model predicts that the Abuloma area's power consumption would increase from 10.076MW in 2023 to 13.73MW in 2035.

Table 3: ANFIS Predicted Monthly and Annual Power Consumption

Year	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec	Ave
2023	10.42	10.21	10.1	10.18	10.26	10.29	10.05	9.56	9.966	10.16	9.919	9.8	10.076
2024	10.81	10.62	10.51	10.56	10.64	10.66	10.41	10.06	10.34	10.45	10.26	10.18	10.458
2025	11.37	11.2	11.1	11.1	11.2	11.19	10.93	10.79	10.89	10.88	10.76	10.73	11.012
2026	11.84	11.7	11.6	11.59	11.69	11.69	11.37	11.32	11.35	11.32	11.22	11.21	11.492
2027	12.56	12.46	12.36	12.35	12.45	12.45	12.04	12.04	12.04	12.04	11.95	11.94	12.223
2028	12.87	12.79	12.69	12.69	12.79	12.79	12.36	12.38	12.37	12.38	12.28	12.27	12.555
2029	12.95	12.85	12.75	12.75	12.85	12.85	12.5	12.5	12.5	12.5	12.36	12.36	12.643
2030	13.04	12.94	12.84	12.84	12.94	12.94	12.66	12.66	12.66	12.66	12.5	12.5	12.765
2031	13.22	13.12	13.02	13.02	13.12	13.12	12.91	12.91	12.91	12.91	12.78	12.78	12.985
2032	13.4	13.3	13.2	13.2	13.3	13.3	13.15	13.16	13.15	13.16	13.07	13.06	13.204
2033	13.6	13.0	13.3	13.4	13.4	13.51	13.42	13.35	13.39	13.18	13.11	13.08	13.312
2034	13.9	13.2	13.5	13.5	13.7	13.3	13.3	13.4	13.5	13.2	13.1	13.3	13.42

								5	5		5	3	
2035	14.2	14.1	14.0	13.5	13.5	13.9	13.87	13.48	13.6	13.77	13.39	13.5	13.73

Table 4: ANN Predicted Monthly and Annual Average Power Consumption

Year	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec	Ave
2023	11.02	10.9	10.87	10.86	10.83	10.74	10.79	10.3	10.47	10.61	10.57	10.35	10.67
2024	11.9	11.87	11.9	11.92	11.89	11.75	11.58	11.75	11.89	11.89	11.77	11.9	11.84
2025	12.19	12.2	12.25	12.29	12.31	12.31	12.24	12.13	12.3	12.43	12.43	12.37	12.29
2026	12.27	12.3	12.36	12.4	12.42	12.43	12.41	12.33	12.51	12.63	12.61	12.57	12.44
2027	12.29	12.34	12.39	12.43	12.45	12.46	12.47	12.44	12.6	12.72	12.71	12.65	12.5
2028	12.3	12.35	12.41	12.44	12.46	12.47	12.5	12.51	12.64	12.77	12.77	12.71	12.52
2029	12.31	12.37	12.42	12.45	12.46	12.48	12.52	12.58	12.68	12.79	12.81	12.78	12.55
2030	12.33	12.38	12.43	12.45	12.47	12.48	12.54	12.65	12.73	12.81	12.83	12.82	12.58
2031	12.34	12.4	12.44	12.46	12.47	12.49	12.55	12.7	12.78	12.82	12.84	12.84	12.6
2032	12.35	12.41	12.44	12.46	12.47	12.49	12.56	12.75	12.83	12.83	12.82	12.84	12.61

2033	12.6	12.34	12.31	12.65	12.32	12.64	12.87	12.84	12.89	12.94	12.9	12.98	12.69
2034	12.8	12.34	12.61	12.65	12.72	12.84	12.87	12.94	12.99	12.94	12.9	12.98	12.79
2035	13.3	13.14	13.87	12.95	12.9	12.94	12.97	12.97	12.99	12.91	12.94	12.99	13.07

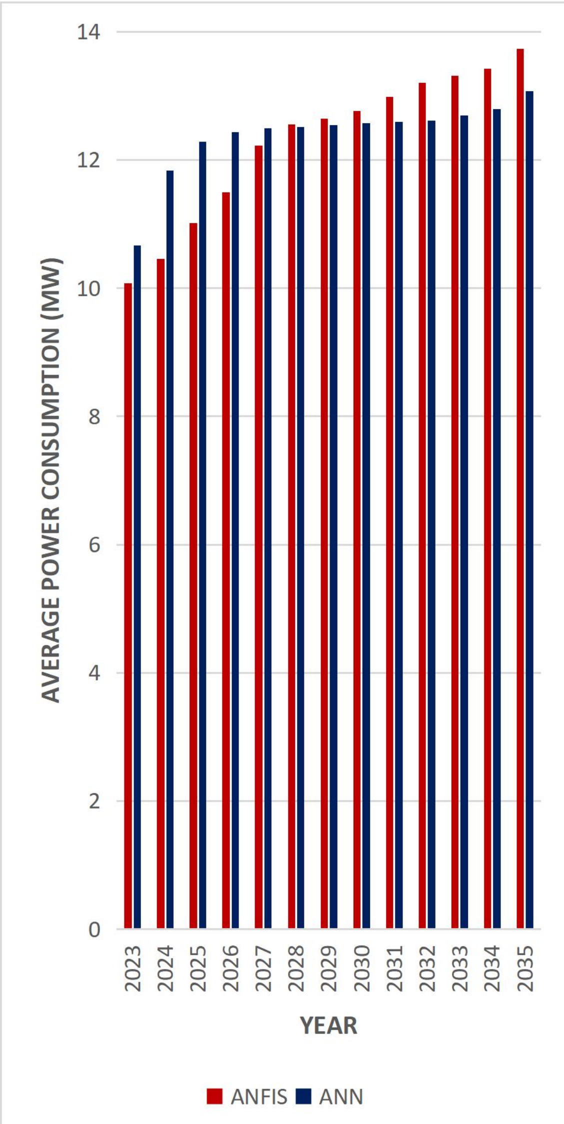

Fig. 6: A graph of predicted average power consumption using ANFIS and ANN models

. The regression results for the ANN **5.0**

Conclusion

This paper focuses on electrical load forecasting utilizing ANFIS and ANN. Abuloma 33/11kV Injection Substation serves as the distribution network for this investigation. A 13-year forecast of electricity usage for 2023–2035 was completed. In order to forecast future power usage, the ANFIS and ANN models were designed and simulated. The minimal mean squared error (MSE) for the training of ANFIS is 0.307983 and the training was completed at epoch 2 whereas, the MSE for ANN model is 0.3201 at epoch 10. ANFIS model performed better in predicting the power consumption training, validation and testing were 0.9289, 0.9262 and 0.9501. The regression results showed that there is a close fit between the actual data and the neural network results. The actual power consumption data of Abuloma 33kV Injection Substation from 2010 to 2022, showed that there was an increase in power consumption from 4.9MW to 9.1MW and the predicted power consumption rose from 10.076MW in 2023 to 13.73MW in 2035 using ANFIS model.

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