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Fuzzy Expert System Model for Prediction of Electric Load Demand-Supply Balance: A Review

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ABSTRACT

Electricity load prediction is fundamentally needed in the electricity business as unit commitment decision is paramount in order to reduce wastages and maximize profit. The purpose of this study is to integrate Supply Required Factors (SRF) as identified by this study to the existing parameters used (such as temperature, humidity, rainfall, sun intensity, previous load history, time of the day, weekdays, weekends and holidays) in predicting electricity demand using a fuzzy logic approach. The SRFs are standard of living of the area under consideration and historical bill payment of the area. Rainstorm is also integrated in addition to SRF as most developing countries still use overhead power lines which is greatly affected by rainstorm. The integration of the SRF parameters will aid in predicting electricity load that is affordable to the consumers thereby balancing the supply with demand.

Keywords: Fuzzy Expert System, Load prediction, Demand, Artificial Intelligence

1.0 INTRODUCTION

1.1 Background of the study

The demand for electricity continues to be a vital part of the backbone of any modern society; whether economically or socially. Almost all human activities depend on electrical energy to provide their needed services Etukudor (2015). The advances in technologies and the diversification on the demand of electrical energy have put excessive pressure on the DisCos (Distribution Companies). According the Minister of Works and Power, as reported in the Advisory Power Team, Office of the Vice President & Power Africa, (2015), the Transmission Company has the capacity to generate over 7000MW of electricity. However, what is eventually distributed to homes and offices is considerably lesser by a long stretch.

It is a known fact that the total power generated by the combined Generation Companies is far below what is required to power Nigeria. To compound on the inadequacy of power generation, the TCN have severally failed to deliver power to the right location as might be required by the DisCos. Similarly, the DisCos sometimes fail to deliver power to the designated customers due to inefficiency in some of the

equipment such as the distribution transformer. This is a result of the problem of transformer overload and vandalization. (Usman , 2010).

Load forecasting is the estimation of future active loads at various load buses ahead of actual load occurrence (Ali et al., 2016). Load forecasting has become a tremendous tool for effective and sustainable power system management. It also plays a vital role in the overall operations of power systems such as unit commitment, schedule maintenance, hydro-thermal scheduling as well as security assessment (Ertugrul, 2016).

Furthermore, the dependency on electrical energy requires a thorough managerial decision in order to ensure that the generated energy is fully utilized. Also, decision regarding where and when to drop electric power is characterised by a lot of uncertainties and ambiguities as making such decisions is commonly based on past human experience. Thus, this mostly leads to the attainment of undesirable results. To overcome this problem, a model for forecasting electric load and voltage control using step-2 Fuzzy logic was adopted by Le, (2016). The study succeeded to automatically regulate electric voltage control system in distribution setup and periodically forecast short term electric load demand in some

selected location. It thus, providing a real time algorithm that provide instantaneous solution to problem such as unit commitment decision.

2.0 REVIEW OF RELATED WORKS

Das, Annaqeeb, Azar, Novakovic, and Kjærgaard, (2020) considered temperature, relative humidity and device consumption pattern as input parameters in predicting a day and a week ahead, the electric load demand of a building based on the state-of-the-art deep learning. Three models were developed namely: Miscellaneous Energy Loads (MEL), Long-Short Term Memory (LSTM) and Bidirectional Long-Short Term Memory (Bi-LSTM). The results were compared and the Bi-LSTM was significantly better than the LSTM particularly when predicting a long period of time. The result can contribute immensely in managing the energy of a building for effective utilization of energy. However, the uncertainty in the number of parameters, variation in the type of building as well as the fact that individual may have a control of share resources in offices must have impacted the result.

In an attempt to determine the relationship between temperature changes and the consumption of electric power, Salehizade (2015) posited that temperature and new year holiday are the two main factors that affect load consumptions. He also found that electric load consumptions depend on air temperature and that for every increase in the temperature of 6°C, the average load on network increases by 207MW. To this end, it can be inferred that, increase in atmospheric temperature equally leads to the rise in electricity demand.

Recently, Artificial intelligence methodologies have taken a centre stage in load prediction as evidently shown in the work of (Bala & Pindoriya, 2021). The authors developed fuzzy-based ensemble model using a hybrid deep neural network (Radial Basis Function Neural Network (RBFNN) and Convolutional Neural Network (CNN)) to predict the electricity load of a given location. The study identifies three important input parameters for load prediction namely: latest load observation, maximum daily temperature and calendar data (hourly, monthly and special data index such as weekend or celebrated public holidays). The input for the

model as implemented using Gaussian MF, are load time series and temperature time series. The model was divided into three layers namely: fuzzy clustering, RBFNN and aggregation layers. The study succeeded in predicting hourly load demand for the next seven days. The result shows a significant improvement on the state-of-the-art and the traditional forecasting method. However, a one-step training procedure would have improved the result as against the two-step training procedure adopted by the study.

Electric load prediction is divided into three classes as opined by Barman et al. (2017). They include:

- i. Short-Term Load Prediction: load prediction that is not more than one week
- ii. Medium-Term load Prediction: load prediction that spans up to a period of one month
- iii. Long-Term Load prediction: prediction that ranges from a few months to several years.

2.1 Short Term Load Prediction

Short term load prediction is a type of load forecasting with an estimated time period starting from one hour ahead to seven days ahead (Ali et al., 2016). Short term load prediction has proven to improve the reliability of power distribution system with emphasis on unit commitment. In an attempt to predict the load demand for one day ahead, Manoj and Shah (2015) considered three factors namely: time, forecasted temperature and the load of a similar previous day to predict Short Term Load Forecasting (STLF) and apply fuzzy set techniques in the load classification. The relationship between several inputs and their corresponding output may be non-linear. However, for simplicity, a linear relationship was adopted for the research. Although several approaches exist to represent the membership function, the rectangular membership function was used for both input and output.

Additionally, Time as one of the input to the fuzzy system is further divided into seven triangular membership function as follows: Mid Night; Dawn; Morning; Noon; Evening; Dusk and Night. For varied degree of temperature, triangular membership function is used to further divide temperature into: very very low (VVL); very low (VL); low (L); normal (N); high (H); very high (VH) and very very high (VVH). The

similar previous day load is divided in 17 triangular membership function. The simulation was conducted using MATLAB and the results shows error in prediction as minimal as the percentage error in any case was less than 2.

Electric load demand during holidays tend to vary with the non-holiday period. Çevik and Çunkas (2016), predict load demand during holidays, classifying the Turkish holidays into:

- i. National holidays
- ii. National Sunday holidays
- iii. Preparation day of religion holidays
- iv. Religion holidays

The study used different approach, compared to others, in predicting load demand as weather parameter was not considered as usual input in the modelling of Turkey's load demand during holidays. Two models were developed based on the following inputs, model1: previous year's holiday data, previous load and the type of holidays (national and religion). The previous year's holiday data was scaled into five membership functions of VL, L, N, H and VH for the second model. Otherwise, all other inputs are the same. Although, date of national holidays remained unchanged, the date of religion holidays changes. In both cases, the two models designed were based on the hourly load for the year 2009, 2010 and 2011. These models were used to predict the 2012 electric load demand of Turkey during holidays. The actual load was compared with the predicted results and accuracy was measured using Mean Absolute Percentage Error (MAPE) value for the models as follows: model1 is 5.57% and model2 is 5.34%. The result shows that, the prediction from models were very close to the actual load, however, model2 has less percentage error as compared to model1.

Seasonal demand varies in almost all facets of human endeavour. Such variation ranges from the type of cloth we wear, the type of food we eat as well as the electric load demand we require. Additionally, electric load demand prediction aids in scheduling maintenance, unit load commitment to a location and other operational maintenance in power system. (Akil & Mitani, 2018) used a fuzzy method in predicting 24 hours load demand in a tropical region for two seasons in Massaka, Indonesia. The periods under consideration are 28 Jan., 2014 to 15 March, 2014 (Raining season) and 13 June, 2014 to 23 August, 2014 (Dry season). Due to the variation in the

meteorological conditions from one period of time to another, two separate models were proposed: the Dry season model and the Raining season model. The dry season model has one of its inputs as Time of load and this it was divided into 9 triangular membership function as follows; Mid night, Dawn, Morning, Forenoon, Noon, Afternoon, Early evening, Evening and Night. The second input is the Temperature and this was also divided into 3 Gaussian functions as follow: Below normal, Normal and Above normal. The final input in the model is Type of day which was also divided into two membership function namely: Holiday period and Non Holiday period. While the Raining season model has 4 inputs that include all inputs from the Dry season model plus Rainfall. The output of the model is the estimated load demand for the respect season. MAPE and Mean Percentage error (MPE) were used in analysing the results, MAPE show that error for Holiday and non-holidays period in the dry season model were 2.74% and 2.94% respectively, which indicate that the prediction is good (Hahn, Meyer-Nieberg, & Pickl, 2009). The MPE for the dry season model for non-holiday and holiday period was -0.42% (underestimation) and 1.75% (over estimation) respectively.

Moreover, MAPE show that error for Holiday and non-holidays period in the dry season model are 2.37% and 2.74% respectively, which indicate that the prediction is good (Hahn, Meyer-Nieberg, & Pickl, 2009). In both cases, MAPE shows that the prediction for holiday period yield better results indicating that the load demand during holidays period is less than the load consumption during the non-holidays period. The MPE value in raining season model, show that both load estimation are under estimated. The study also show that the prediction for raining season model is better than the prediction for the dry season model.

Most prediction of electrical load demand using statistical method uses weather parameter which naturally has lots of uncertainty, this affect greatly the correctness of the prediction. To this end Mahmuda, (2013), considered few years' data by classifying the data into similar day and their heuristics rule in developing a model to predict electric load demand, to handle the uncertainty associated with weather parameter, Min-Max algorithm was used. Although, Least

Square Multiple Regression Analysis (LSMRA) was initially used to predict load with Temperature and Humidity as the key inputs, temperature Forecasted Error (TFE) as well as error between sampled points were obtained. Mean Absolute Error (MAE) shows that the percentage difference for the load forecasting for Actual Temperature (AT) and the Forecasted Temperature (FT) is 0.86%.

Load prediction for both AT and FT show percentage error greater than 5% which is not a good prediction (Hahn et al., 2009), to overcome the excessive error. The error is managed by assigning five fuzzy membership functions for the Temperature (Very Low, Low, Normal, High and Very High) to reduce the Temperature Forecasted Error (TFE). Mean Average Error (MAE) indicate a considerably improvement in the LSMRA as the result from fuzzy logic method show 1.18% as against 5.58% (result from LSMRA), this further show the strength of fuzzy method in load prediction over the statistical method.

To improve unit commitment decision and to reduce the cost of generating electrical power as well as to improve the reliability in Transmission and Distribution, Ali et al., (2016) used Time, Temperature and similar previous days record as the independent variables supplied to a fuzzy control system. They show that analysis of the characteristics of electric load and critical factors that determine load consumption are very important factors in determining load requirement of a given location. The fuzzy system was simulated using the MATLAB, this is worth noting as the result illustrate how fuzzy method successfully predict electric load demand of a location for one day ahead which is vital in unit commitment decision and other critical decision by the stakeholder(s). Also worthy to note is that, the error in the fuzzy control system developed was between the 12.14% to -9.48% which suggest the need to continue improved on the rule base as well as further evaluation of the factors that determine load consumption.

To reinstate the popularity and the strength of one of the two Artificial Intelligence (AI) technique in forecasting electric demand, Manoj and Shah, (2015) developed two model using Fuzzy logic and Artificial Neural Network (ANN). Both

model used Temperature, Time and load of previous similar day as inputs through Fuzzification and the input layer respectively. 381 rules were developed for the fuzzy logic model and about 200 neurons were trained in hidden layers of the ANN architecture for the ANN model, and base on the fact that, if a substation is working correctly in the previous similar day and experience a shutdown on the day of prediction, they subtract the megawatt supplied by the substation so as to get the final forecast for the day. Error analysis of the two AI technique show that fuzzy logic outperform the ANN method as the curve of fuzzy method is closer to the actual load than that of the ANN method. The result further elaborate that the fuzzy method is easier to develop than the ANN method.

However, the inputs variables used for both model did not cover wide range of factors that affect the consumption of electric load. Increasing the number of variable that affect load consumptions will have positive effect on the prediction, although, these factors as the case may be, could have varied degree depending on the geographical location of where the forecast is carried out. (Konica & Hanelli, 2016)

In order to forecast the electricity load demand of a given location (Ganguly & Zayegh 2017) used two inputs parameter for a fuzzy model. The study considered time of the day which was divided into twelve membership function and day types and was divided into weekdays and weekends. The results shows the effectiveness of fuzzy logic approach in electricity load prediction as the forecasted load has minimal error. The results further show the dependency of weekend load prediction on the previous load rather than the forecasted load while the forecasted load for weekdays depends greatly on the forecasted load. However, considering just two parameters in predicting electric load demand could produce ineffective results as other factors such as temperature, relative humidity as well as sun intensity would have improve the accuracy of the prediction. Additionally, the inference engine consists of just twenty four rules which is significantly low for making smart decision.

Ibrahim et al. (2021) argued that trapezoidal Membership function (MF) outperformed triangular membership function while trying to

predict short term electricity load. The study show that the mean forecast error (MFE) is 0.4292 for trapezoidal MF and 2.4917 for triangular membership function and argued that fuzzy logic is most ideal short term electricity load prediction. However, considering that only temperature, time and previous load history were used in order to compare the performance of trapezoidal MF and trigonometry MF, adding more parameters such as sun intensity, rainfall, standard of living of the location as well as bill payment pattern would have improved the accuracy of the results.

The overview of previous study based on the inputs parameters using artificial intelligence technique availed that Benson and Ogunjuyigbe (2018) considered temperature, humidity and previous load history for short term load prediction. Similarly, Islas et al. (2021) used temperature, humidity, time of the day, weekday, weekend/holiday, average past load, load demand for past day and past week to modelled hourly electric load demand. The study revealed that fuzzy logic result outperformed neural network result. Likewise, Ahmad et al. (2020) only considered previous load history of three years (January, 2017 to December, 2019) to predict short term electric load demand using support vector machine and extremely learning machine. Tudose, Picioroaga, Sidea, Bulac, and Boicea (2021) added covid-19 data to the previous used data such weather parameters, holidays in determine demand using Convolutional Neural Network. In a like manner, Kumar and Hans (2018) considered time and previous load history in predicting electricity load demand based on fuzzy logic. Indistinguishably, Madrid and Antonio (2021) employed weather parameters, holidays and previous load history in predicting short term electricity load using machine learning. In a similar fashion, Panda, Ray, and Mishra, (2021) also used previous load and weather parameter in determining electricity load needs using metaheuristic techniques.

2.2 Medium Term Load Prediction

Most research conducted using fuzzy logic method in predicting electric load demand considered one or two climatic condition notably, temperature and humidity with other factors such as time, day type. Barman et al., (2017) considered several climatic condition such as

“forecasted temperature of the day to be predicted, forecasted humidity of the day to predicted, forecasted wind speed plus similar day average load demand and the type of day (holiday and non-holiday)”. The authors availed these condition to model a fuzzy control system (to predict medium term load forecast) that base on heuristic, is capable to incorporate human reasoning and intuition. They opine that, there are three stages of fuzzy logic implementation process.

- i. Input and output parameter should be assigned value
- ii. Assigning rules that control the fuzzy system
- iii. Executing the fuzzy inference by correctly mapping the input to an output

Winter (Jan., 2016) and summer (July, 2016) data were used to developed two model using fuzzy logic method and the ANN. Moreover, load deviation was computed using MAPE, fuzzy logic method percentage error for winter and summer are 1.67%, 1.06% respectively while the percentage error for winter and summer for ANN model is 2.58% and 2.19% respectively. Crucially, the results suggest that fuzzy logic method outperformed the ANN method. However, the work fail to demonstrate the process used to arrive at the ANN result.

2.3 Long Term Load Forecasting

It is worthy to determine the relationship between electric load demand and others factors that may directly or indirectly affect electric load consumption. Ali, Yohanna, Puwu, and Garkida, (2016) in their work to predict long term load forecasting, use weather parameter, temperature and humidity as the input to the fuzzy control system to forecast one year ahead load demand, and establish that load increase with increase in temperature but increase in humidity do not have much effect on the load. The model was developed using Simulink MATLAB. MAPE and APE were used for error analysis and in both case, the error is 6.9% with a success rate of 93.1% which they regard as being efficient and accurate for long term load forecasting. This is not withstanding that Hahn et al., (2009) submit that any percentage error greater than 5% is not good. The work also established that weather parameter has effect on the electric load but the relationship between them may vary because of

the variation in weather parameter from one location to another.

3.0 CONCLUSION

The research work addresses the limitation of the previous studies in predicting electric demand by proposing a model that is not only dependent on the environmental factors such as temperature, humidity, rainfall, sun intensity or previous load history and time of the day or season, weekdays and weekends but also considers some novel variables which this study consider Supply Required Factor (SRF). The SRFs are the standard of living of unit area and bill payment history. Incorporating the SRFs to the exogenous factors as used by previous studies will enable the proposed model to predict electric load that is affordable to the consumers. Additionally, the SRFs will balance the supply of electricity with the demand for it, thereby reducing the huge debt by the consumers as characterised by the developing countries (Nigeria). In addition, this study introduced another new parameter in predicting load demand based on artificial intelligence method (Rainstorm). This variable is incorporated due to the overhead electricity power lines. This overhead power transmission is inexpensive as compared to the underground. However, they are easily affected by rainstorm which if not foreseen, will result in the wastage of electricity as the distribution company might be supplied with the load that they may not have resources to utilize. The model applies fuzzy logic method by identifying the input variables and uses fuzzy scaling method to create the linguistics variables associated with each input variable in order to predict the electric load demand of a given location. This work will significantly reduce the ATC&C being the total difference between the amount of electricity received by DisCos from the TCN and the amount of electricity for which it invoices its customers and the adjusted collection loss.

REFERENCES

- Advisory Power Team, Office of the Vice President, F. G. of N., & Power Africa. (2015). Nigeria Power Baseline Report. In *Federal Government of Nigeria*. Retrieved from <https://mypower.ng/wp-content/uploads/2018/01/Baseline-Report.pdf>
- Ahmad, W., Ayub, N., Ali, T., Irfan, M., Awais, M., Shiraz, M., & Glowacz, A. (2020). Towards short term electricity load forecasting using improved support vector machine and extreme learning machine. *Energies*, 13(11), 1–17. <https://doi.org/10.3390/en13112907>
- Akil, Y. S., & Mitani, Y. (2018). Seasonal Short-Term Electricity Demand Forecasting under Tropical Condition using Fuzzy Approach Model. *Journal of Telecommunication, Electrical and Computer Engineering*, 9(1), 77–82.
- Ali, A. T., Tayeb, E. B. M., & Shamseldin, Z. M. (2016). Short Term Electrical Load Forecasting Using Fuzzy Logic. *International Journal Of Advancement In Engineering Technology*, 03(11), 131–138.
- Ali, D., Yohanna, M., Puwu, M. I., & Garkida, B. M. (2016). Long-term load forecast modelling using a fuzzy logic approach. *Pacific Science Review A: Natural Science and Engineering*, 18(2), 123–127. <https://doi.org/10.1016/j.psra.2016.09.011>
- Bala, S. K. P., & Pindoriya, N. M. (2021). Demand response in consumer-Centric electricity market: Mathematical models and optimization problems. *Electric Power Systems Research*, 193(June 2020), 106923. <https://doi.org/10.1016/j.epsr.2020.106923>
- Barman, M., Choudhury, N. B. D., & Behera, S. (2017). A fuzzy logic controller based mid-term load forecasting with renewable penetration in Assam, India. *ADB Journal of Engineering Technology*, 6(3), 1–6.
- Benson, S. A., & Ogunjuyigbe, J. K. (2018). Impact of weather variables on electricity power demand forecast using fuzzy logic technique. *Nigerian Journal of Technology*, 37(2), 450. <https://doi.org/10.4314/njt.v37i2.21>
- Çevik, H. H., & Çunkas, M. (2016). A fuzzy logic based short term load forecast for the holidays. *International Journal of Machine Learning and Computing*, 6(1), 57. <https://doi.org/10.18178/ijmlc.2016.6.1.572>
- Das, A., Annaqeeb, M. K., Azar, E., Novakovic, V., & Kjærgaard, M. B. (2020). Occupant-centric miscellaneous electric loads prediction in buildings using state-of-the-art deep learning methods. *Applied Energy*, 269(February), 115135. <https://doi.org/10.1016/j.apenergy.2020.115135>
- Ertugrul, Ö. F. (2016). Forecasting electricity load by a novel recurrent extreme learning

- machines approach. *International Journal of Electrical Power and Energy Systems*, 78, 429–435.
<https://doi.org/10.1016/j.ijepes.2015.12.006>
- Etukudor, C. (2015). *The Daunting Challenges of the Nigerian Electricity Supply Industry*. 5(9), 25–33.
- Ganguly, Piyali; Zayegh, A. (2017). Short Term Load Forecasting using Fuzzy Logic. *Melecon*, (October), 1470–1473.
https://doi.org/10.1007/978-1-4613-1073-0_9
- Hahn, H., Meyer-Nieberg, S., & Pickl, S. (2009). Electric load forecasting methods: Tools for decision making. *European Journal of Operational Research*, 199(3), 902–907.
<https://doi.org/10.1016/j.ejor.2009.01.062>
- Ibrahim, O., Owonikoko, W. O., Abdulkarim, A., Otuoze, A. O., Afolayan, M. A., Madugu, I. S., ... Adedayo, K. E. (2021). Performance evaluation of different membership function in fuzzy logic based short-term load forecasting. *Pertanika Journal of Science and Technology*, 29(2), 959–978.
<https://doi.org/10.47836/pjst.29.2.14>
- Islas, M. A., Rubio, J. de J., Muñoz, S., Ochoa, G., Pacheco, J., Meda-Campaña, J. A., ... Zacarias, A. (2021). A fuzzy logic model for hourly electrical power demand modeling. *Electronics (Switzerland)*, 10(4), 1–12.
<https://doi.org/10.3390/electronics10040448>
- Konica, J. A., & Hanelli, L. (2016). Forecasting Next-Day the Electricity Demand Based On Fuzzy Logic Method Case for Albania. *Management*, 3(12), 6172–6180. Retrieved from
<https://pdfs.semanticscholar.org/f355/4ed50a3694dfd161215ccf54dbbecf376c4f.pdf>
- Kumar, M., & Hans, S. S. (2018). Load Forecasting using Fuzzy Logic Tool Box. *GRD Journals-Global Research and Development Journal for Engineering*, 3(8), 12–19. Retrieved from www.grdjournals.com
- Le, C. (2016). *Type-2 Fuzzy Logic System Applications for Power Systems*. (December).
- Madrid, E. A., & Antonio, N. (2021). Short-term electricity load forecasting with machine learning. *Information (Switzerland)*, 12(2), 1–21. <https://doi.org/10.3390/info12020050>
- Mahmuda A Monne, K. S. A. (2013). *Application of Fuzzy logic to Electric Load Forecasting (ELF)*. 3(12), 47–50. Retrieved from [http://www.ijstat.com/admin/download/Application of Fuzzy logic to Electric Load Forecasting ELF.pdf](http://www.ijstat.com/admin/download/Application%20of%20Fuzzy%20logic%20to%20Electric%20Load%20Forecasting%20ELF.pdf)
- Manoj, P. P., & Shah, A. P. (2015). Fuzzy Logic Methodology for Short Term Load Forecasting. *International Journal of Research in Engineering and Technology*, 03(04), 322–328.
<https://doi.org/10.15623/ijret.2014.0304058>
- Panda, S. K., Ray, P., & Mishra, D. P. (2021). Short Term Load Forecasting using Metaheuristic Techniques. *IOP Conference Series: Materials Science and Engineering*, 1033(1). <https://doi.org/10.1088/1757-899X/1033/1/012016>
- Salehizade, A. A. (2015). *Analysis of Temperature Changes on Electricity Consumption in Fars Province*. 6(3), 610–617.
<https://doi.org/10.5901/mjss.2015.v6n3s2p610>
- Tudose, A. M., Picioroaga, I. I., Sidea, D. O., Bulac, C., & Boicea, V. A. (2021). Short-term load forecasting using convolutional neural networks in covid-19 context: The Romanian case study. *Energies*, 14(13).
<https://doi.org/10.3390/en14134046>
- Usman, H., & Polytechnic, K. (2010). *Major Factors Affecting Electricity Generation, Transmission And Distribution In Nigeria Sule, A. H. 1*, 159–164.