Prediction Of Power Demand In Nigeria Using Particle Swamp/Trust-Region Optimization And Fuzzy Inference System

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***Abstract*— Electricity power demand forecasting plays a substantial role in the administration and balance of current power system. For this reason, accurate prediction of service demand are needed to develop better programing for the generation and distribution of power and to reduce the vulnerabilities in the integration of an electric power system. The prediction of power demand in Nigeria using particle swamp/trust region optimization and fuzzy inference system was applied to identify the type of model with the highest accuracy forecasting power demand in Nigeria, two classes of forecasting models where compared statistical models (econometric models of Harvey, exponential smoothing, auto regression model) is compared to Intelligence System (FUZZY Inference System). Furthermore the use of hybrid optimization model of trust region and particle swam optimization that have made significant contribution to electric power demand forecasting was identified and a case study is applied to compare with the intelligence system of (FIS). Among our main finding we conclude that the Intelligence System gave a better prediction performance than the Econometric Models.**

Keywords—Prediction, Optimization, Power Demand, Particle Swamp Optimization/Trust Region, Comparison, Fuzzy Inference System

1.1 INTRODUCTION

Energy is vital for the sustainable development of any country. Over the past decade, global energy demand has grown exponentially. Energy is correlated with industrial production, agricultural production, nutrition, water access, economy, employment, quality of life [3], Accurate forecasting of electricity load is crucial for formulating the planning and operational strategies of power generation , transmission and distribution systems. Unit commitment and scheduling of power plant significantly depends on the precise forecast of load [15].

The ability to forecast accurately the load demand a few hours ahead is beneficial from different points of view, ranging from technical to commercial. This importance has led to the development of several mathematical models/techniques. These techniques can be broadly classified as classical time series model and machine intelligence models [16]. This gives the power utility company an idea about the future demand of the consumers an ample amount of time to mitigate the difference between the generation capacity and load demand. Demand prediction minimizes the power generation cost and helps to establish an organized power system utility, especially because of the large expense pertaining to power generation. [1] Different Machine Learning (ML) based techniques are widely used by many power and energy utility companies to predict the power or energy needed to equilibrate between generation and demand. In general, load forecasting can be termed as a technique for demand and supply management [10].

Electricity supply in Nigeria dates back to 1886 when two small generating sets were installed to serve the then colony of Lagos. By an act of parliament in 1951, the Electricity Corporation of Nigeria (ECN) was established and in 1962, the Niger Dams Authority (NDA) was also established. However, a merger of the two was made in 1972 to form the National Electric Power Authority (NEPA) as a result of unbundling and power reform process, it was renamed Power Holding Company of Nigeria (PHCN) in 2005 [14]. In February 2005, the World Bank agreed to provide PHCN with $100 million to assist in its privatization efforts. In November 2013, the Federal government of Nigeria (FGN) concluded the privatization of power sector in Nigeria which led to selling of the PHCN to some privately owned companies. Nigeria is a country blessed with a lot of resources such as coal, oil, natural gas, water and other renewable energy sources that can be used to generate electricity; and the renewable energy being solar energy, biomass, wind, small and large hydropower with potential for hydrogen fuel, geothermal and ocean energies.

Nigeria is Africa's major oil producing country which accounts for two-thirds of Africa's crude oil reserves. Talking about Nigerian natural gas reserves, it is estimated to be 187.44 trillion standard cubic feet in 2005 [8]. These reserves are known to be substantially larger than its oil reserves in terms of energy. Gas utilization for generation of electricity is said to be a primary goal for Nigeria. The first discovery of coal was in the year 1909; the mining began in 1916 with a recorded output of about 24,500 tons [12]. The poor industrialization and varying economic growth in Nigeria may be attributed to unreliable and inadequate power supply. The socio-economic development activities in the country are responsible for the increase in demand for electricity. Mostly, this high demand can be found in the manufacturing and commercial sub-sectors. The problem of Nigeria appears to be lower electricity supply compared to the electricity consumption.

As at 2007, Nigeria has about 14 generating plants with an installed capacity of 7,876MW but the installed available capacity is less than 4000MW as at 2009. Nigerian electricity supply market has a lot of potential profit to investors if they invest in the generation, transmission and distribution of electricity. Generation of electric power in Nigeria is overwhelmed by excessive demand for electricity by consumers because of inadequate supply. This supply shortfall has resulted into unannounced load shedding, prolonged and intermittent power outages supplies to the consumers over the years. The total amount of electricity generated in Nigeria as at August 2013 dropped to 2,628.6 Megawatts [7]. Traditional financial models start with the Black Scholes assumption of the Geometric Brownian Motion or log-normal prices. This assumption does not make sense in the context of electricity prices for many reasons including the non-predictability of electricity prices. A model which has been used in practice is known as the Ornstein-Uhlenbeck process. This is a continuous time model which permits autocorrelation. It is necessary to incorporate mean reversion when modeling electricity prices because of the electricity price jumps due to unexpected events. Basically, there are three stages involved in the business of electricity; these stages are the generation, transmission and distribution of electricity. Power generation, transmission and distribution involve flow of currents with heat losses in conductors. These losses can be reduced through better design, construction and maintenance.

In this study, regression modeling that involves tuning of the least square generated regression coefficient with trust region and particle swarm linear search algorithm was determined for various econometric models with the best model selected for load forecast.

1.2 Review of Related Literature

Modern power system demands an uninterrupted supply of electricity to the load side, this requires a proper idea of predicting present and future load demand with least amount of error for achieving this goal, scientist and scholars have been trying to develop the most efficient and optimal state of the art method for predicting the future demand for electricity consumption by a method known as load forecasting. [5]

Load forecasting is used is to control several operations and decision, such as dispatch, unit commitment, fuel allocation and off line network analysis. [8]

Some of these researcher are Annamareddi *et al* (2013), Shafiul *et al* (2021) and Saranya *et al* (2020)

[6] utilised annual energy consumption data from national bureau of statistics which accounts for the amount of energy consumed between 2000 to 2012 for industrial commercial and residential, the author use econometric model considering only rhe effect of time

$Y_t = a_0 + a_1 T$ (1)

Where Y_E is the energy consumed, T is the time and a_0 and a_1 are the regressors.

However the author utilise only time and sum of square error method to evaluate the performance and (57%).

[4] Proposal a long term electric power load forecast of twenty years in Nigeria using modified form of

exponential regression model which was implemented in matlah platform

$Y_t = e^{a+} (X_t)$ (2)

Equation (2) as proposed by [16] the linear form is presented as in equation (3)

$\ln Y_t = a + bX_t$ (3)

Where X_t is the independent variables parameter time, Y_t represent each of the load (commercial, industrial and residential) and a & b on the coefficient which estimated based on data obtained

The author utilise an energy consumption data between 2000 to 2012 and mean absolute percentage error to evaluate the prediction accuracy and arrive at a result of 92.3%

1.3 Research Procedure

It is important to note that a great deal of effort is required in ensuring constant electricity supply in Nigeria to ensure industrial growth leading to increase in financial viability of the nation. To achieve this, four econometric models as proposed by previous studies are utilized in this research. The models include;

Harvey, auto-regressive, exponential and fuzzy inference model (FIS). The first three models are classified as econometric empirical model with the four being and econometric artificial intelligent model. Data containing the primary factors which includes time, temperature and population values and required output of industrial, residential and commercial load demand were obtained Nigeria Bureau of Statistics (NBS) of CBN but sent from the national control center in Oshogbo. The input and the output variables of the data was applied to the econometric models to generate the regressors (coefficient variables) of each model with least square method MatLab 2021 a. With the regressors, predictions were made and compared to the model tunned with the hybrid of trust region and particle swarm linear search methods. Also, the same procedure was carried with FIS model to obtain the required membership functions and inference rules that yield the maximum prediction accuracy and compared with the prediction performance obtained from the empirical models using sum of square errors and R-square statistics are the prediction performance evaluation parameters.

The best model was selected and utilized in carrying the forecast for monthly load demand from October 2022 to December 2025. Since future temperature and population are not known, a linear model that generates high prediction efficiency was utilized in extrapolating the temperature and population varies taking cognissance of the available data for previous months.

The summary of the research procedure is presented in the flow diagram shown in Figure 1

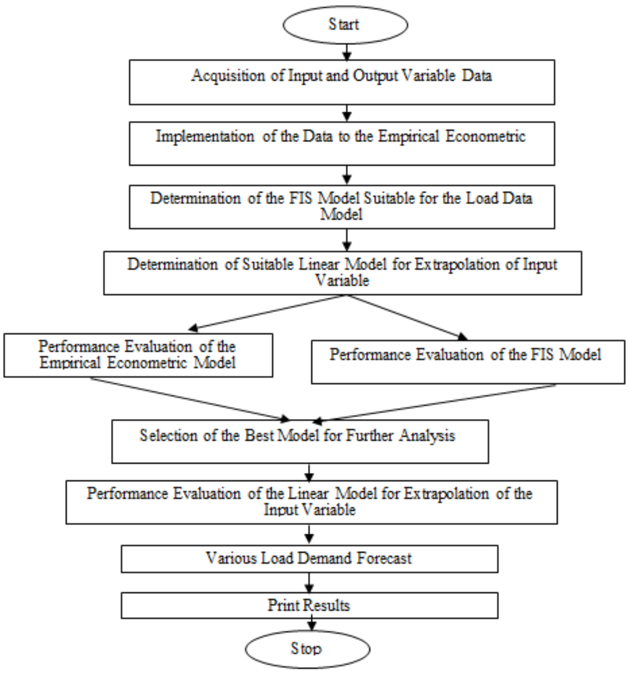

Figure 1: The Flow Chat of the Research Procedure.

1.4 Empirical Econometric Models

The empirical models utilized in this study includes; Harvey model, exponential smoothing model and auto-regressive model.

The Harvey model proposed by [17] previous studies is given as;

$\ln y_t = a \ln Y_{t-1} + b + ct$ (4)

With the introduction of temperature and population, the modified model becomes;

$$\ln Y_t = a \ln Y_{t-1} + bt + cP + dT \quad (5)$$

where Y_t is the various load demand, Y_{t-1} is the load demand with one year lag, t is the time, P is the population, T is the temperature and a to d are the regression coefficients to be obtained.

The auto-regressive model as proposed by [2] is given as;

$Y_t = a + bY_{t-1}$ (6)

Taking into cognizance, the introduction of population and temperature, Equation (6) becomes.

$Y_t = a + bY_{t-1} + cP + dT$ (7)

The exponential smoothing model is given as;

$Y_t = aY_t + (1-a)Y_t$ (8)

This model utilizes only load demand one year lag as the input parameter. To account for the input parameters, two separate smoothning models must be introduced to account for the temperature and population variables. The model is shown in Equations (9) and (10) for the temperature and population respectively.

$$Y_t = bT + (1-b)T \quad (9)$$
$$Y_t = cP + (1-c)P \quad (10)$$

It should be noted that the coefficients variables a, b and c must have values between 0 to 1.

To determine the coefficient of the empirical econometric models with least square method.

1.5 Performance Evaluation

This is to determine the measure of prediction of the models utilized in the prediction of the load demands. The measure used in determining the model accuracy includes; SSE and R-square value. SSE is given as;

$$SSE = \sum (Y_a - Y_p)^2 \quad (11)$$

To determine the R-square value, the sum of square residual (SSR) is obtained which is given as;

$$SSR = \sum (Y_p - Y_{am})^2 \quad (12)$$

The R-square value is given as;

$$R - square = 1 - \frac{SSE}{SSR} \quad (13)$$

where Y_p is the predicted load demand, Y_a is the actual load demand and Y_{am} is the mean of the actual load demand.

The model with the least SSE and highest R-square was selected for the load forecast. After generating the coefficient variables, the model undergoes further tunning using a hybrid of trust region and particle swarm tunning techniques.

1.6 Results and Discussion

The R-square values for Harvey model tuned with least square method and Trust-Region/PSO is shown in Figure 2

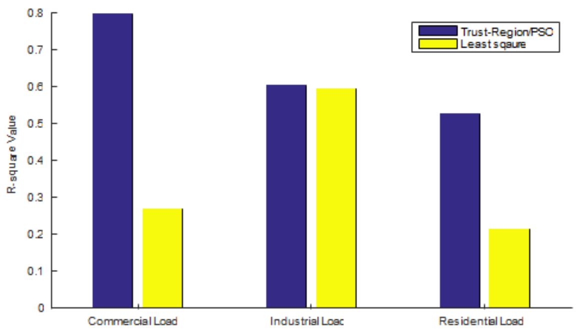

Figure 2: R-square values for the loads tuned with different techniques.

Auto Regressive Model

The R-square values for Auto-regressive model tuned with least square method and Trust-Region/PSO is shown in Figure 3

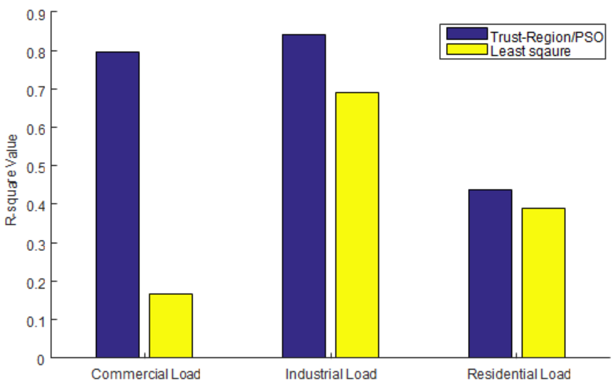

Figure 3: R-square values for the loads tuned with different techniques.

Exponential Smoothing Model

The plot indicating the R-square values of the least square method and hybrid trust region/ PSO for the commercial load, industrial load and residential load is shown in Figure 4

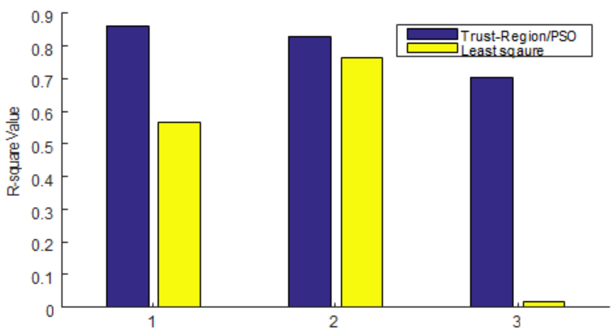

Figure 4: R-square values for the loads tuned with different techniques.

From the bar charts shown in Figure 2, Figure 3 and Figure 4 for Harvey model, auto-regressive model and exponential smoothing model respectively, it can be seen that the model coefficient tuned with hybrid of trust region and particle swarm had a better prediction performance than that tuned with least squared method. Therefore to select the best model, the R-square value of the econometric models tuned with trust-region/PSO technique is displayed in Figure 5, Figure 6 and Figure 7 for commercial load, industrial load and residential load respectively.

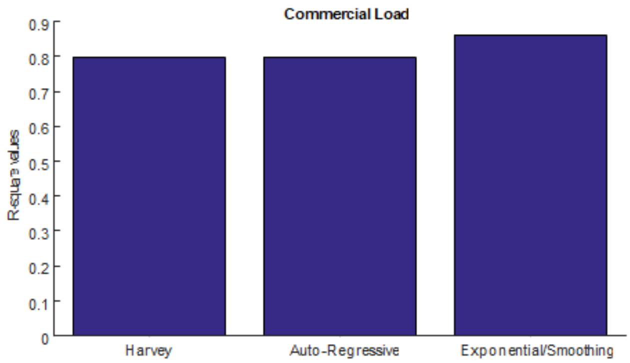

Figure 5: R-square values of the econometric models for commercial load.

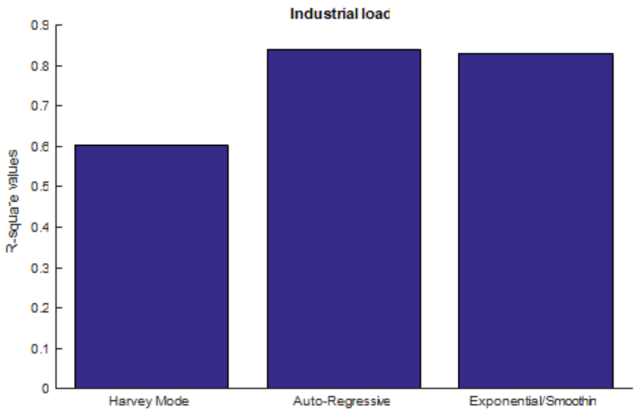

Figure 6: R-square values of the econometric models for industrial load.

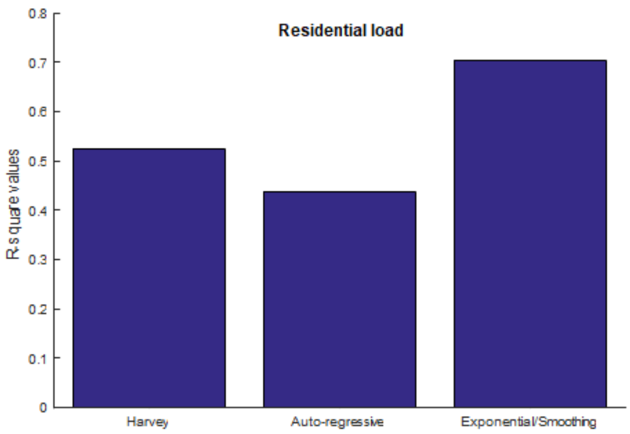

Figure 7: R-square values of the econometric models for Residential load.

From the figures displayed in Figure 5, Figure 6 and Figure 7, it can seen that Exponential smoothing model had the best prediction for the commercial load and residential load while the Auto-regressive model had the best prediction performance for the industrial load. The models selected were tuned with trust-region/PSO method.

1.7 Fuzzy Inference System

A bar chart showing the R-square values of the prediction performance with fuzzy logic is shown in Figure 8

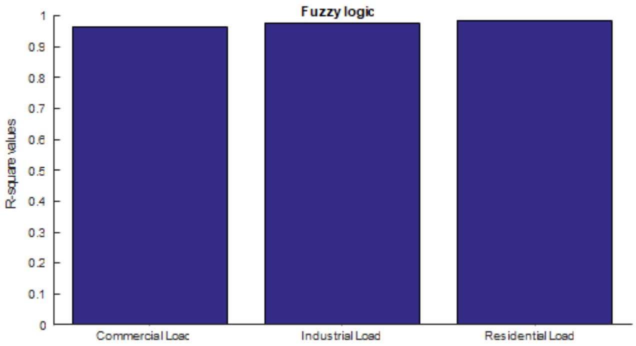

Fig. 8: R-square values at different loads.

A comparative chart of R-square values with econometric model and fuzzy logic is shown in Figure 9

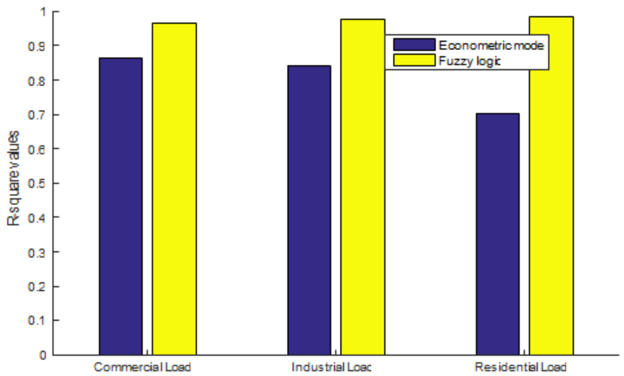

Figure 9: Comparative Analysis of econometric models and Fuzzy logic.

From Figure 9, it can be seen that fuzzy logic had a better prediction performance than the econometric models. Hence, the fuzzy logic model was utilized for the load forecast.

1.8 Load Forecast

Fuzzy logic model being the best model in terms of prediction performance was used for the extrapolation of the input variable data (population and temperature) and then applied for the load forecast which commences from December 2021 to December 2040. The outcome is shown in Table 1. Since the last data obtained was in august 2021 which was 200th week, the extrapolation will commence from 201st week.

Table 1: Data forecast Result

Time (Months)	Population	Temperature	Commercial Load	Industrial Load	Residential Load
201	140.5	34.8	3945	8500	9985
202	140.56	34.806	3948	8509.2	9996.6
203	140.63	34.813	3951	8518.4	10008
204	140.69	34.819	3954.1	8527.6	10020
205	140.75	34.826	3957.1	8536.8	10032
206	140.82	34.832	3960.1	8546	10043
207	140.88	34.838	3963.1	8555.1	10055
208	140.94	34.845	3966.1	8564.3	10066
209	141.01	34.851	3969.2	8573.5	10078
210	141.07	34.857	3972.2	8582.7	10090
211	141.13	34.864	3975.2	8591.9	10101
212	141.2	34.87	3978.2	8601.1	10113
213	141.26	34.877	3981.3	8610.3	10125
214	141.32	34.883	3984.3	8619.5	10136
215	141.38	34.889	3987.3	8628.7	10148
216	141.45	34.896	3990.3	8637.9	10160
217	141.51	34.902	3993.3	8647.1	10171
218	141.57	34.909	3996.4	8656.3	10183
219	141.64	34.915	3999.4	8665.4	10194
220	141.7	34.921	4002.4	8674.6	10206
221	141.76	34.928	4005.4	8683.8	10218
222	141.83	34.934	4008.4	8693	10229
223	141.89	34.94	4011.5	8702.2	10241
224	141.95	34.947	4014.5	8711.4	10253
225	142.02	34.953	4017.5	8720.6	10264
226	142.08	34.96	4020.5	8729.8	10276
227	142.14	34.966	4023.6	8739	10288
228	142.21	34.972	4026.6	8748.2	10299
229	142.27	34.979	4029.6	8757.4	10311
230	142.33	34.985	4032.6	8766.6	10323
231	142.4	34.991	4035.6	8775.7	10334
232	142.46	34.998	4038.7	8784.9	10346
233	142.52	35.004	4041.7	8794.1	10357
234	142.59	35.011	4044.7	8803.3	10369
235	142.65	35.017	4047.7	8812.5	10381
236	142.71	35.023	4050.7	8821.7	10392
237	142.77	35.03	4053.8	8830.9	10404
238	142.84	35.036	4056.8	8840.1	10416
239	142.9	35.043	4059.8	8849.3	10427
240	142.96	35.049	4062.8	8858.5	10439
241	143.03	35.055	4065.9	8867.7	10451
242	143.09	35.062	4068.9	8876.9	10462
243	143.15	35.068	4071.9	8886	10474
244	143.22	35.074	4074.9	8895.2	10485
245	143.28	35.081	4077.9	8904.4	10497
246	143.34	35.087	4081	8913.6	10509
247	143.41	35.094	4084	8922.8	10520
248	143.47	35.1	4087	8932	10532

1.9 Discussion of Result

In the current investigation econometric models (Harvey models, Auto regression model and exponential smoothing model) is compared to that of machine learning a Fuzzy Inference System (FIS). In the prediction of power demand (residential, industries and commercial) the econometric model used where turned with the coefficient of trust region and particular swamp techniques with the performance evaluation of sum of square error and root square method, to obtain the following result.

Table 2: Performance result of econometric models

Models	Commercial Load	Industrial	Residential
Harvey	0.8	0.6	0.55
Auto Regression	0.8	0.8	0.45
Exponential	0.85	0.8	0.70

Table 3: Comparing the performance of econometric models and machine learning models.

Models	Commercial Load	Industrial	Residential
Econometric	0.85	0.85	0.55
Machine learn	0.95	0.95	0.98

From the table above it is deduced that the machine learning algorithm FIS which presents a better forecasting result. It is also important to note that the result of the hybrid optimized models were better than those that were not optimized Ezenaya *et al*. (2016) utilized the linear that account for only time us the deterministic factor heading to the prediction accuracy (R Square volume) of 0.57. Ezenaya *et al*. (2016) studied the effect of climate change on load demand using auto regressive model and maple accuracy of 0.93 which is a better improvement Dikkio *et al*. (2018). Presented a long term electric power load forecast using the modified exponential regressive model to arrive at an accuracy of 89.23%.

However in my own investigation I compared with the performance of the econometric model (optimize with hybride) and machine learning to arrives at R-Square accuracy volume of 95.0% for commercial load, 95.0% for industrial and 98.0 for residual load which present a more reliable result.

1.10 Conclusion and Future Works

Since fuzzy inference system has a better and higher forecasting accuracy, it should be pointed that the forecast carried out with fuzzy logic model should be utilized for the planning of the power generation and distribution system. It can also be seen that the accuracy of forecasting carried out with the hybrid of trust region and particle swarm optimization is more accurate than those done with exponential smoothing, auto-regressive model and harvey model being the most accurate. Therefore, the model tunned with the hybrid trust region and particle swarm optimization should be used.

Suggestion for Further Study

i. Peak load forecast with econometric models tunned with bee colony optimization technique.

ii. Peak load forecast with adaptive neuro fuzzy inference system (ANFIS)

iii. 3Peak load forecast with econometric models tuned with non-linear tuning technique

.1.11 Conflict of Interest

The authors declares that there is no conflict of interests regarding the publication of this manuscript.

1.12 Abbreviation

*ECN*Electricity Cooperation of Nigeria
*FIS*Fuzzy Inference System
*ML*Machine Learning
*NDA*Niger Dams Authority
*NEPA*National Electricity Power Authority
*PSO*Particle Swamp Optimization
*SSE*Sum of Square Error

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