Adaptive Neuro-Fuzzy Inference System (ANFIS) Model for Forecasting and Predicting Industrial Electricity Consumption in Nigeria

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Abstract The main aim of this paper is to model the industrial power consumption in Nigeria with the Adaptive Neuro-Fuzzy Inference System (ANFIS) model and then forecast the industrial power consumed for the next five years beyond the available data. About 45 years (1970 to 2015) dataset was obtained from the Central Bank of Nigeria (CBN), the National Bureau of Statistics (NBS) and other relevant organizations. The data includes population, rainfall, electricity connectivity and temperature which are the explanatory variables. Matlab was used along with the dataset to train and evaluate the ANFIS model which was then used to forecast the industrial power consumption in Nigeria for the years 2016 to 2020. The prediction performance of the ANFIS model was compared to those of Autoregressive Moving Average model and Moving Average model. From the result obtained, ANFIS gave R-square value of 0.9977 (99.77%), SSE value of 395.3674 and RMSE value of 2.9641. The regression coefficient of 99.77% shows that about 99.77% of the variations in the industrial power consumption in Nigeria for the years 1970 to 2015 are explained by the selected explanatory variables. The forecast result showed that the Nigerian industrial power consumption would be about 374.7 MW at the end of 2020 which is about 73.1% increase from the industrial power consumption in 2015. As such, based on the industrial power consumption in 2015, over 73% increment in power supply to the industrial sector will be required to satisfy the industrial sector's power demand in 2020.

Keywords Industrial Power Consumption, Adaptive Neuro-Fuzzy Inference System (ANFIS), Energy Forecast, Electricity Connectivity, Fuzzification, Membership Function

1. Introduction

Forecasting is the act of making prediction of future events and situations. In different areas of life, forecasting is the basic technique of decision making targeted at minimizing risk in decision making and reducing unanticipated cost [1, 2, 3]. Accordingly, in the power industry, correct prediction of future load demand enables power utility companies to supply electrical energy to the consumers economically. Particularly, it allows power utilities companies to plan their operations such as unit commitment and generator maintenance beforehand, and thus, serve their customers with more reliable and more economically efficient electric power [4, 5, 6, 7]. This has become important seeing that energy resources are often limited along with challenges emanating from environmental factors [8, 9, 10, 11, 12]. Studies have shown that geographical location, population, social factors and weather factors have different impacts on power systems [11, 12, 13, 14, 15, 16]. Therefore, accurate load forecasting model that takes into consideration the essential factors that do affect the power demand pattern is important in power system planning.

Consequently, in this paper Adaptive Neuro-Fuzzy Inference System (ANFIS) technique is used to model and forecast the industrial electricity consumption in Nigeria [16, 17, 18, 19, 20]. This has become necessary as Nigerian government is focused on diversifying its economy by facilitating more indigenous technologies, expanding its small and medium scale enterprises and attracts more foreign investments [21, 22, 23, 24, 25, 26]. ANFIS which is a kind of artificial neural network that is based on Takagi-Sugeno fuzzy inference system was developed in the early 1990s [27, 28, 29, 30, 31, 32, 33]. ANFIS integrates both neural networks and fuzzy logic principles and it has the potential to capture the benefits of both neural networks and fuzzy logic in a single framework [34, 35, 36, 37, 38].

One of the advantages of fuzzy systems is that they describe fuzzy rules, which fit the description of the real-world processes to a greater extent [2, 39, 40, 41, 42, 43, 44]. Another advantage of fuzzy systems is their interpretability; it means that it is possible to explain why a particular value appeared at the output of a fuzzy system. In view of its salient attributes, ANFIS has been employed in a number of studies including those concerning load forecasting [45, 46, 47, 48, 49].

2. Methodology

2.1. Collection of Data

In this paper Adaptive Neuro-Fuzzy Inference System (ANFIS) is used in modeling the industrial electricity consumption in Nigeria and then to forecast the industrial electricity consumption in Nigeria from 2016 to 2020. The 45 years (1970-2015) data used in the study was collected from various publications of the Central Bank of Nigeria (CBN) and the National Bureau of Statistics (NBS). The

data collected include: industrial electricity consumption, temperature, connectivity, population and rainfall. The data is given in Table 1.

The raw data is normalized to within the range of 0.1 to 0.9 using the equation.

$$x_{norm} = \frac{x}{x_{max}} \quad (1)$$

where x_{norm} is the normalized data of the original values of the explanatory variables, x is the raw values of the explanatory variables (temperature, rainfall, population, connectivity and actual industrial electricity consumption). x_{max} is the maximum value of the explanatory variables (temperature, rainfall, population, connectivity and actual industrial power consumption). This normalized form is chosen because it tends to provide a better outcome on the Predicted Industrial Power Consumption (Predicted IPC). About 60 percent (60%) of the original data was used as training dataset whereas 40 percent (40%) of the dataset was used as the validation dataset.

Table 1. Data from National Bureau of Statistics (NBS) and Central Bank of Nigeria (CBN)

Time (years)	Temperature (°C)	Population	Rainfall (mm)	Connectivity (% of population)	Industrial Electricity Consumption (MW)
1970	26.8690	56131844	93.2474	22	91.4000
1971	26.4121	57453734	90.8679	22	114.9000
1972	26.9176	58829319	87.6959	22	138.2000
1973	27.2231	60285453	81.2038	22	146.1000
1974	26.2714	61857023	94.4808	25	163.2000
1975	26.2194	63565598	96.4250	25	200.4000
1976	26.3880	65426976	91.4644	25	214.6000
1977	26.4934	67425435	86.9932	25	253.0000
1978	26.5287	69512233	101.4315	25	157.7000
1979	26.9335	71619216	96.8826	30	160.3000
1980	26.8761	73698096	100.0646	30	199.7000
1981	26.7763	75729572	91.5726	30	121.0000
1982	26.8601	77729802	85.6780	30	262.0000
1983	27.0519	79729311	73.0148	30	254.4000
1984	27.1845	81775215	89.0549	30	217.2000
1985	26.9894	83901570	88.5841	30	259.8000
1986	27.0078	86118043	88.4083	30	280.5000
1987	27.5971	88412917	82.7691	30	294.1000
1988	27.0661	90773613	94.7851	30	291.1000
1989	26.4981	93179755	91.6024	30	257.9000
1990	27.4483	95617345	89.0172	33	230.1000
1991	27.0546	98085436	97.5072	33	253.7000
1992	26.6130	100592458	90.8569	33	245.3000
1993	27.0105	103145093	95.7557	33	237.4000
1994	26.7261	105753088	97.6496	33	233.3000
1995	27.1357	108424822	95.4165	35	218.7000
1996	27.1161	111164651	101.9210	35	235.3000
1997	27.0780	113975055	99.6741	35	236.8000
1998	27.6369	116860691	96.2221	35	218.9000
1999	27.0768	119826231	101.3462	35	191.8000
2000	26.8463	122876723	93.7123	38	223.8000
2001	26.9931	126014935	88.3470	38	241.9000
2002	27.2266	129246283	90.4583	38	146.2000
2003	27.3791	132581484	102.6651	40	196.0000
2004	27.3415	136033321	96.4417	40	398.0000
2005	27.4817	139611303	87.1168	40	182.3000
2006	27.4051	143318011	95.9864	40	307.8320
2007	27.4265	147152502	101.0405	41	296.3450
2008	27.1349	151115683	109.3087	41	184.7520
2009	27.8538	155207145	94.2806	41	230.9290
2010	27.9143	159424742	94.9717	41	127.6150
2011	29.6265	163770669	80.2430	42	150.6303
2012	24.7959	168240403	101.8373	42	105.0084
2013	24.0816	172816517	79.0466	42	166.1961
2014	27.9760	177475986	114.1960	42	145.0290
2015	26.9710	182201962	163.5670	43	216.4920

2.2. Development of the Adaptive Neuro-Fuzzy Inference System (ANFIS) Model

Four unique inputs namely temperature, rainfall, population and electricity connectivity which were the explanatory variables were used in this work. Also, one output, the industrial power consumption was used in this work. The input data are converted to degrees of memberships and membership values in a process called fuzzification. The triangular membership function was used for the four inputs as well as the output. Each of the four inputs was divided into three triangular membership functions. Also, the output was divided into three triangular

membership functions. The input variables (explanatory variables) and the output variables were imported to the ANFIS environment via the workspace key after clicking on load data. The outcome of these commands can be seen in Figure 1. Fuzzification process was performed in the MATLAB FIS editor and the outcome is given in Figure 2. The ANFIS structure is given in Figure 3 which shows the four input neurons with each neuron connected to three membership functions as it is also in the fuzzy part of the system. Membership function for each of the explanatory variables is shown in Figure 4 to Figure 7. The number of fuzzy logic rules used was two hundred and forty-six (246) as shown in Figure 8.

Figure 1. Graphic User Interface of ANFIS with input and output parameters

Figure 2. Graphic User Interface for fuzzy logic representation

Figure 3. Graphic User Interface of the ANFIS model structure for industrial power consumption forecasting.

Figure 4. Membership function for the temperature variable.

Figure 5. Membership function for the rainfall variable.

Figure 6. Membership function connectivity variable

Figure 7. Membership function for population variable.

Figure 8. Fuzzy logic Rules

The ANFIS graphic user interface showing the error of the epoch is shown in Figure 9, while Figure 10 shows the checking of the ANFIS predicted data. According to Figure 9, after simulating the system under 40 epochs (40 iterations), with the normalized dataset the error of the ANFIS system at the 40th iteration was 0.00076577, after checking (Figure 10), the minimal error was 0.61265. With this minimal error of 0.00076577, it shows that the ANFIS can be used to effectively predict the industrial power consumption in Nigeria.

Figure 9. ANFIS Graphic User Interface showing the error of the epochs

Figure 10. Checking of the ANFIS predicted data

The performance measures used to evaluate the developed model are the regression coefficient or coefficient of determination (R^2), the root means square error (RMSE) and the sum of square errors (SSE). The Root Mean Square Error (RMSE) is given as follows;

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (2)$$

where: Y_i is the actual industrial electricity consumption and $\hat{Y}_i$ is the predicted value from the model. The Root Means Square Error (RMSE) is given as;

$$RMSE = \sqrt{MSE} \quad (3)$$

The formula for the sum of square error (SSE) is given as;

$$SSE = \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (4)$$

2.3. Other Models Considered

The prediction performance of the ANFIS model was compared to that of two other regression models namely, Autoregressive Moving Average Model and Moving Average Model. The models are developed from the same dataset used for the training of the ANFIS model. The autoregressive moving average model is expressed as follow;

$$Y_t = -921.3945 - 0.8569Y_{t-1} + 247.9828\varepsilon_{t-1} \quad (5)$$

The moving average model is expressed as follows;

The moving average model for predicting industrial power consumption is given as:

$$Y_t = -218.2246 + 81.3846\varepsilon_{t-1} \quad (6)$$

Where ε_{t-1} is $\ln Y_{t-1}$

3. Results and Discussions

Table 2 shows the normalized data for the prediction of industrial electricity consumption in Nigeria with Adaptive-Neuro Fuzzy Inference System (ANFIS) model and the normalized ANFIS model predicted industrial power consumption in Nigeria for the years 1970 to 2015. Table 3 and Figure 11 show actual industrial power consumption in Nigeria (MW) and the ANFIS model predicted industrial power consumption in Nigeria for the years 1970 to 2015.

Based on Table 3 and Figure 11, the regression coefficient between the actual industrial power consumed and the ANFIS model predicted industrial power consumed is 0.9977 (99.77%), the SSE is 395.3674 and RMSE is 2.9641. The regression coefficient of 99.77 % shows that about 99.77% of the variations in industrial power consumption in Nigeria for the years 1970 to 2015 are explained by the selected explanatory variables.

Table2. Normalized data for the prediction of industrial electricity consumption in Nigeria with Adaptive-Neuro Fuzzy Inference System (ANFIS) model and the normalized ANFIS model predicted industrial power consumption in Nigeria for the years (1970 to 2015)

Time (years)	Normalized Temperature	Normalized Population	Normalized Rainfall	Normalized Connectivity	Normalized Actual Industrial Electricity Consumption	Normalized Predicted Industrial Power Consumption
1970	0.9069	0.3081	0.5701	0.5116	0.2296	0.2302
1971	0.8915	0.3153	0.5555	0.5116	0.2887	0.3140
1972	0.9086	0.3229	0.5361	0.5116	0.3472	0.3458
1973	0.9189	0.3309	0.4965	0.5116	0.3671	0.3670
1974	0.8868	0.3395	0.5776	0.5814	0.4101	0.4145
1975	0.8850	0.3489	0.5895	0.5814	0.5035	0.5076
1976	0.8907	0.3591	0.5592	0.5814	0.5392	0.4758
1977	0.8943	0.3701	0.5319	0.5814	0.6357	0.6422
1978	0.8955	0.3815	0.6201	0.5814	0.3962	0.3966
1979	0.9091	0.3931	0.5923	0.6977	0.4028	0.4330
1980	0.9072	0.4045	0.6118	0.6977	0.5018	0.4555
1981	0.9038	0.4156	0.5598	0.6977	0.3040	0.3793
1982	0.9066	0.4266	0.5238	0.6977	0.6583	0.6106
1983	0.9131	0.4376	0.4464	0.6977	0.6392	0.6340
1984	0.9176	0.4488	0.5445	0.6977	0.5457	0.5447
1985	0.9110	0.4605	0.5416	0.6977	0.6528	0.6622
1986	0.9116	0.4727	0.5405	0.6977	0.7048	0.7109
1987	0.9315	0.4852	0.5060	0.6977	0.7389	0.7399
1988	0.9136	0.4982	0.5795	0.6977	0.7314	0.7192
1989	0.8944	0.5114	0.5600	0.6977	0.6480	0.6896
1990	0.9265	0.5248	0.5442	0.7674	0.5781	0.5752
1991	0.9132	0.5383	0.5961	0.7674	0.6374	0.6125
1992	0.8983	0.5521	0.5555	0.7674	0.6163	0.5867
1993	0.9117	0.5661	0.5854	0.7674	0.5965	0.6349
1994	0.9021	0.5804	0.5970	0.7674	0.5862	0.5791
1995	0.9159	0.5951	0.5833	0.8140	0.5495	0.5517
1996	0.9153	0.6101	0.6231	0.8140	0.5912	0.5948
1997	0.9140	0.6255	0.6094	0.8140	0.5950	0.5851
1998	0.9329	0.6414	0.5883	0.8140	0.5500	0.5515
1999	0.9140	0.6577	0.6196	0.8140	0.4819	0.4838
2000	0.9062	0.6744	0.5729	0.8837	0.5623	0.5624
2001	0.9111	0.6916	0.5401	0.8837	0.6078	0.6104
2002	0.9190	0.7094	0.5530	0.8837	0.3673	0.3605
2003	0.9242	0.7277	0.6277	0.9302	0.4925	0.5007
2004	0.9229	0.7466	0.5896	0.9302	1.0000	0.9863
2005	0.9276	0.7662	0.5326	0.9302	0.4580	0.4683
2006	0.9250	0.7866	0.5868	0.9302	0.7734	0.7777
2007	0.9258	0.8076	0.6177	0.9535	0.7446	0.7465
2008	0.9159	0.8294	0.6683	0.9535	0.4642	0.4641
2009	0.9402	0.8518	0.5764	0.9535	0.5802	0.5593
2010	0.9422	0.8750	0.5806	0.9535	0.3206	0.3334
2011	1.0000	0.8988	0.4906	0.9767	0.3785	0.3790
2012	0.8370	0.9234	0.6226	0.9767	0.2638	0.2638
2013	0.8129	0.9485	0.4833	0.9767	0.4176	0.4176
2014	0.9443	0.9741	0.6982	0.9767	0.3644	0.3649
2015	0.9104	1.0000	1.0000	1.0000	0.5439	0.5439

Table 3. The actual industrial power consumption in Nigeria (MW) and the ANFIS model predicted industrial power consumption in Nigeria for the years 1970 to 2015

Time (years)	Actual Industrial Electricity Consumption in Nigeria (MW)	Predicted Industrial Power Consumption (MW) in Nigeria (MW)
1970	91.4	91.6
1971	114.9	125.0
1972	138.2	137.6
1973	146.1	146.1
1974	163.2	165.0
1975	200.4	202.0
1976	214.6	189.4
1977	253.0	255.6
1978	157.7	157.8
1979	160.3	172.3
1980	199.7	181.3
1981	121.0	151.0
1982	262.0	243.0
1983	254.4	252.3
1984	217.2	216.8
1985	259.8	263.6
1986	280.5	282.9
1987	294.1	294.5
1988	291.1	286.2
1989	257.9	274.5
1990	230.1	228.9
1991	253.7	243.8
1992	245.3	233.5
1993	237.4	252.7
1994	233.3	230.5
1995	218.7	219.6
1996	235.3	236.7
1997	236.8	232.9
1998	218.9	219.5
1999	191.8	192.6
2000	223.8	223.8
2001	241.9	242.9
2002	146.2	143.5
2003	196.0	199.3
2004	398.0	392.5
2005	182.3	186.4
2006	307.8	309.5
2007	296.3	297.1
2008	184.8	184.7
2009	230.9	222.6
2010	127.6	132.7
2011	150.6	150.8
2012	105.0	105.0
2013	166.2	166.2
2014	145.0	145.2
2015	216.5	216.5

Figure 11. Comparison of the actual industrial power consumed and ANFIS model predicted industrial power consumed in Nigeria for the years 1970 to 2015

The comparison of the actual industrial power consumed with the Autoregressive moving average model predicted industrial power is shown in Figure 12. Also, the comparison of the actual industrial power consumed with the moving average model predicted industrial power is shown in Figure 13. The prediction performance of the three models considered in this paper is shown in Table 4. The results in Table 4 show that among the three models the ANFIS model has the best prediction performance. In this study, the ANFIS model was developed (trained) using 60% of the dataset which consist of the data from 1970 to 2001. Also, the ANFIS model was validated using 40% of the dataset which consist of the data from 2002 to 2015. Again, Table 4 shows that the prediction performance of the ANFIS model with respect to the training data and also with respect to the validation data are very good. As such, the ANFI model was used to forecast the industrial electricity consumption in Nigeria from 2016 to 2020. The ANFIS forecast result is shown in Figure 14 and Table 5. From Figure 14, Nigeria shall witness the least industrial power consumption in October of 2017 with a total industrial power consumption of about 323.2 MW. The Nigerian industrial power consumption will be about 374.7 MW at the end of 2020. This is about 73.1% increase from the industrial power consumption in 2015. As such, based on the last published industrial power consumption in 2015, over 73% increment in power supply to the industrial sector will be required to satisfy the industrial sector's power demand in 2020.

Figure 12. Comparison of the actual industrial power consumed with Autoregressive moving average model predicted industrial power

Figure 13. Comparison of the actual industrial power consumed with moving average model predicted industrial power consumed

Table 4. Prediction performance of the three models along with the ANFIS performance based on the training and validation datasets

Models	R-Square	SSE	RMSE
Auto-Regressive (1970 -2015 dataset)	0.1485 (14.85%)	133820	54.5322
Moving Average(1970 -2015 dataset)	0.1839 (18.39%)	128240	53.3841
ANFIS (1970 -2015 dataset)	0.9977(99.77%)	395.3674	2.9641
ANFIS Training Data (1970 -2001 dataset)	0.9992 (99.92%)	395.3674	2.4225
ANFIS Validation (2002 -2015 dataset)	0.9974(99.74%)	395.3674	3.1613

Table 5. The five years forecast of the industrial power consumption in Nigeria using ANFIS model

Time (Years)	Temperature($^{\circ}$ C)	Rainfall (mm)	Population	Connectivity (%)	Forecasted Industrial Power consumed (MW)
2016	26.8210	96.0532	185330100	41.0	391.0
2017	27.3320	102.4870	188219552	42.0	339.5
2018	27.1920	88.3310	191233001	44.0	323.2
2019	28.1390	109.8310	193154212	43.0	377.0
2020	27.1330	90.6190	196017022	41.5	374.7

Figure 14. Forecast of Industrial Power Consumption in Nigeria for five years (2016 to 2020) with ANFIS model

4. Conclusions

Development and evaluation of Adaptive Neuro-Fuzzy Inference System (ANFIS) model for characterizing the industrial power consumption in Nigeria is presented. About 45 years data on industrial power consumption in Nigeria, population, rainfall, electricity connectivity and temperature was obtained relevant organisations where population, rainfall, electricity connectivity and temperature are the explanatory variables. Matlab was used along with the dataset to train and evaluate the ANFIS model which was then used to forecast the industrial power consumption in Nigeria for the years 2016 to 2020. The prediction performance of the ANFIS model was compared to those of Autoregressive Moving Average Model and Moving Average Model. In all the results obtained, ANFIS gave very high and acceptable R-square value which showed that about 99.77 % of the variations in industrial power consumption in Nigeria for the years 1970 to 2015 are explained by the selected explanatory variables. The forecast result showed that based on the industrial power consumption in 2015, over 73 % increment in power supply to the industrial sector will be required to satisfy the industrial sector's power demand in 2020.

REFERENCES

- [1] Dong, X., Lu, H., Xia, Y., & Xiong, Z. (2016). Decision-Making Model under Risk Assessment Based on Entropy. *Entropy*, 18(11), 404.
- [2] Ghore, S., & Goswami, A. (2015) Short Term Load Forecasting of Chhattisgarh Grid Using Adaptive Neuro Fuzzy Inference System. *International Journal of Science and Research (IJSR)* Volume 4 Issue 11, November 2015
- [3] Amlabu, C. A., Agber, J. U., Onah, C. O., & Mohammed, S. Y. (2013). Electric Load Forecasting: A Case Study of the Nigerian Power Sector. *International Journal of Science Engineering and Innovative Technology*, 2, 23-27.
- [4] Awosope, C. (2015). Nigeria Electricity Industry: Issues, Challenges and Solutions.
- [5] Paaso, E. A., & Liao, Y. (2013). Development of New Algorithms for Power System Short-Term Load Forecasting. *Development*, 2(02).
- [6] Baharudin, Z., & Kamel, N. (2008, December). Autoregressive method in short term load forecast. In *Power and Energy Conference, 2008. PECon 2008. IEEE 2nd International* (pp. 1603-1608). IEEE.
- [7] Burns, S., & Gross, G. (1990). Value of service reliability. *IEEE Transactions on Power Systems*, 5(3), 825-834.
- [8] Timmons, D., Harris, J. M., & Roach, B. (2014). The economics of renewable energy. *Global Development and Environment Institute, Tufts University*, 52.
- [9] Majano, A. M. (2014). *Study on the development of the renewable energy Market in Latin America and the Caribbean*. Inter-American Development Bank.
- [10] Hughes, B. B., Irfan, M. T., Moyer, J. D., Rothman, D. S., & Solórzano, J. R. (2012). Exploring future impacts of environmental constraints on human development. *Sustainability*, 4(5), 958-994.
- [11] Enete, A. A., & Amusa, T. A. (2010). Challenges of agricultural adaptation to climate change in Nigeria: A synthesis from the literature. *Field Actions Science Reports. The Journal of Field Actions*, 4.
- [12] Riddell, A., Ronson, S., Counts, G., & Spenser, K. (2004). Towards sustainable energy: the current fossil fuel problem and the prospects of geothermal and nuclear power. *Journal on trade & environment-Stanford University, California, USA*.
- [13] Wu, X., Lu, Y., Zhou, S., Chen, L., & Xu, B. (2016). Impact of climate change on human infectious diseases: Empirical evidence and human adaptation. *Environment international*, 86, 14-23.
- [14] Akanni, P. O., Oke, A. E., & Akpomemie, O. A. (2015). Impact of environmental factors on building project performance in Delta State, Nigeria. *HBRC Journal*, 11(1), 91-97.
- [15] Damalas, C. A., & Eleftherohorinos, I. G. (2011). Pesticide exposure, safety issues, and risk assessment indicators.

International journal of environmental research and public health, 8(5), 1402-1419.

- [16] Evans, R. G., & Sadler, E. J. (2008). Methods and technologies to improve efficiency of water use. *Water resources research*, 44(7).
- [17] Patz, J. A., Githeko, A. K., McCarty, J. P., Hussein, S., Confalonieri, U., & De Wet, N. (2003). Climate change and infectious diseases. *Climate change and human health: risks and responses*, 6, 103-37.
- [18] Saravanan, S., Kannan, S., & Thangaraj, C. (2015). Prediction of India's Industrial Sector Electricity Consumption Using ANFIS. In *Power Electronics and Renewable Energy Systems* (pp. 1281-1288). Springer, New Delhi.
- [19] Mamlook, R., Badran, O., & Abdulhadi, E. (2009). A fuzzy inference model for short-term load forecasting. *Energy Policy*, 37(4), 1239-1248.
- [20] Ying, L. C., & Pan, M. C. (2008). Using adaptive network based fuzzy inference system to forecast regional electricity loads. *Energy Conversion and Management*, 49(2), 205-211.
- [21] Adeoye, A. A. (2015). The effect of entrepreneurship on economy growth and development in Nigeria. *International journal of development and economic sustainability*, 3(2), 49-65.
- [22] Chete, L. N., Adeoti, J. O., Adeyinka, F. M., & Ogundele, O. (2014). *Industrial development and growth in Nigeria: Lessons and challenges* (No. 2014/019). WIDER Working Paper.
- [23] Ogechukwu, A. D., & Oboreh, J. S. (2013). Small and medium scale enterprises (SMEs) in Nigeria the marketing interface. *Global Journal of Management and Business Research*.
- [24] Atawodi, O. W., & Ojeka, S. A. (2012). Relationship between tax policy, growth of SMEs and the Nigerian economy. *International Journal of Business and Management*, 7(13), 125.
- [25] Iwuagwu, O. (2011). The cluster concept: Will Nigeria's new industrial development strategy jumpstart the country's industrial takeoff. *Afro Asian Journal of Social Sciences*, 2(2.4), 1-24.
- [26] ECONOMY, I. A. G. (2004, June). Promoting SMEs for Development. In *2 nd OECD Conference of Ministers Responsible for Small and Medium Sized Enterprises (SMEs)* (pp. 3-5).
- [27] Garg, V., Singh, V. P., & Raj, V. (Eds.). (2017). *Development of Water Resources in India* (Vol. 75). Springer.
- [28] Lee, H., Shin, G., Hong, S., Choi, J., & Chun, M. (2016). Post-Chlorination Process Control based on Flow Prediction by Time Series Neural Network in Water Treatment Plant. *International Journal of Fuzzy Logic and Intelligent Systems*, 16(3), 197-207.
- [29] Jaiswal, G. P., & Giri, R. N. (2015). Software Reliability Estimation of Component based Software System using Fuzzy Logic. *International Journal of Computer Science and Information Security*, 13(7), 66.
- [30] Kokkinos, K., Loukas, A., & Samaras, N. (2015). DEVELOPMENT AND EVALUATION OF AN ADAPTIVE NEURO FUZZY INFERENCE SYSTEM FOR THE CALCULATION OF SOIL WATER RECHARGE IN A WATERSHED. *European Scientific Journal, ESJ*, 11(10).
- [31] Xie, H. B., Guo, T., Bai, S., & Dokos, S. (2014). Hybrid soft computing systems for electromyographic signals analysis: a review. *Biomedical engineering online*, 13(1), 8.
- [32] Nauck, D. D., & Nürnberger, A. (2013). Neuro-fuzzy systems: A short historical review. *Computational Intelligence in Intelligent Data Analysis*, (445), 91-109.
- [33] Güler, I., & Übeyli, E. D. (2005). Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients. *Journal of neuroscience methods*, 148(2), 113-121.
- [34] Atia, D. M., & El-madany, H. T. (2017). Analysis and design of greenhouse temperature control using adaptive neuro-fuzzy inference system. *Journal of Electrical Systems and Information Technology*, 4(1), 34-48.
- [35] Saghati, A. H., Zadkarim, S., & Emari, H. (2016). Employee Commitment Prediction in Civil Projects Using Adaptive Neuro-Fuzzy Inference System. *Journal of Current Research in Science*, (2), 326.
- [36] Al Maliky, S., & Sattar, B. (Eds.). (2014). *Multidisciplinary perspectives in cryptology and information security*. IGI Global.
- [37] Tahmasebi, P., & Hezarkhani, A. (2012). A hybrid neural networks-fuzzy logic-genetic algorithm for grade estimation. *Computers & geosciences*, 42, 18-27.
- [38] Kothari, C. R. (2004). *Research methodology: Methods and techniques*. New Age International.
- [39] Kabir, G., & Hasin, M. A. A. (2014). Application of adaptive neuro fuzzy inference system in demand forecasting for power engineering company. *International Journal of Industrial and Systems Engineering*, 18(2), 237-255.
- [40] DC-DC, P. O. N. I. (2011) TO MINIMIZE CURRENT DISTRIBUTION ERROR (CDE) IN PARALLEL OF NON IDENTIC DC-DC CONVERTERS USING ADAPTIVE NEURO FUZZY INFERENCE SYSTEM. *Journal of theoretical and applied information technology* Volume 25 no 1.
- [41] Azar, A. T. (2010). Adaptive neuro-fuzzy systems. *Fuzzy Systems. Vienna, Austria: IN-TECH*, 10, 7220.
- [42] Lim, E. A., & Jayakumar, Y. (2008). A study of neuro-fuzzy system in approximation-based problems. *Matematika*, 24, 113-130.
- [43] Albertos, P., & Sala, A. (1998, September). Fuzzy logic controllers. Advantages and drawbacks. In *VIII International Congress of Automatic Control* (Vol. 3, pp. 833-844).
- [44] Passino, K. M., Yurkovich, S., & Reinfrank, M. (1998). *Fuzzy control* (Vol. 20). Reading, MA: Addison-wesley.
- [45] Santika, G. D., Mahmudy, W. F., & Naba, A. (2017). Electrical Load Forecasting using Adaptive Neuro-Fuzzy

Inference System. *Int. J. Advance Soft Compu. Appl*, 9(1).

- [46] Pal, S., & Sharma, A. K. (2015). Short-Term Load Forecasting Using Adaptive Neuro-Fuzzy Inference System (ANFIS). *Int. Journal of Novel Research in Electrical and Mechanical Engineering*, 2(2), 65-71.
- [47] Bigdeli, N., Afshar, K., Gzafroudi, A. S., & Ramandi, M. Y. (2013). A comparative study of optimal hybrid methods for wind power prediction in wind farm of Alberta, Canada. *Renewable and sustainable energy reviews*, 27, 20-29.
- [48] Xia, J., Zhao, P., & Dai, Y. (2010, October). Neuro-fuzzy networks for short-term wind power forecasting. In *Power System Technology (POWERCON), 2010 International Conference on* (pp. 1-5). IEEE.
- [49] Johnson, P. L., Negnevitsky, M., & Muttaqi, K. M. (2007, December). Short term wind power forecasting using adaptive neuro-fuzzy inference systems. In *Power Engineering Conference, 2007. AUPEC 2007. Australasian Universities* (pp. 1-6). IEEE.