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Forecasting Electric Load Demand Using Hybrid Nonlinear Autoregressive Neural Network with Exogenous inputs and Genetic Algorithm

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Abstract

Electricity demand and supply is a very crucial amenity in running the day to day activities of organizations, business enterprises, government, household, social functions, etc. in the twenty first century. Too much supply of electricity causes wastages and too little causes loss. Forecasting electric load demand is vital as it provides an avenue to reduce wastages and loss on the part of any system that depends upon it in her daily activities. In this paper, an attempt is made to forecast the monthly electric load demand of an automobile assembly plant by the application of hybrid Nonlinear Autoregressive Neural Network with Exogenous Inputs and Genetic Algorithm (NARX-GA). The data set consisted of monthly historical data of Electric Load Demand, Temperature, Relative Humidity and Production records for nineteen years from the year 2000 to 2018. The result from the simulation gave a mean average percentage error (MAPE) of 0.56%. The use of Non Linear Autoregressive Neural Network with Exogenous Inputs and Genetic Algorithm (NARX-GA) optimized models should be encouraged in Utility industries to enhance decision making and planning purposes especially in a deregulated economy.

Keywords: Hybrid Nonlinear Autoregressive, Neural Network, Exogenous Inputs, Genetic Algorithm.

1. Introduction

The socio-technological development of modern economies is hinged on the significant role played by the availability and affordability of electricity. Electricity is a vital source of energy in industries for running industrial machines and related equipment for day to day production activities (Kaseke & Hosking, 2013). Hyndman & Athanasopoulos (2013) defined forecasting as a quantitative technique of estimating future value for decision making. Electricity generated cannot be stored and must be used appropriately by consumers, hence utility industries must generate required electric power to break even and maximize profit. It is of great importance to forecast with high degree of reliability and accuracy the amount of electricity to be generated or the demand capacity in advance. The ability to estimate future values accurately will maximize profit in the long run for the utility company and reduce excessive cost of their produce on the part of the customers. A wrong estimate can lead to excess power being generated or under generated which may lead to loss of revenue by the organization (Walker, 2012). There are several factors that influence the accuracy of estimating a more reliable forecast such as non-deterministic behavior of the consumer, economic and weather factors. Hence, the system must be planned by considering a more reliable load demand estimates so as to generate adequate electric power to meet the demand of the consumers over time. The goal of electric load demand forecasting techniques is to estimate accurate load demands values for future use with high accuracy (Grant, Eltoukhy & Asfour, 2014). Estimating accurate electric load demands in advance is complex due to the influence of extraneous variables such as economic, weather, time and season which has a non-linear relationship with the load demanded (Srivastava, Pandey & Singh, 2016). Phuangpornpitak and Prommee (2016) classified load forecasting into Short-Term Load Forecasting (STLF), Medium-Term Load Forecasting (MTLF) and Long-Term Load Forecasting (LTLF) depending on the forecasting period. Short-Term Load Forecasting considers weekly estimates while Medium and Long-Term forecasts focuses on monthly to yearly forecasting horizon. Peugeot Automobile Nigeria (PAN) Limited established 1974 is located in Kaduna, Nigeria, a company that assembles Peugeot brand of vehicles and market same in Nigeria. The company is supplied with 33KV mains from the Kaduna South injection substation with three 2000MVA generators as backup power supply for daily production operations of the company. The frequent shortage in electricity supply in Nigeria has affected not only the production capacity of PAN but also the cost of production which has been shifted to the consumer (Kaseke & Hosking, 2013). In the 1970s and 1980s, Peugeot automobiles were commonly patronized by government establishments and private companies for official cars. However, due to increase in the cost of buying Peugeot vehicles, government and private companies sort for alternatives. This decision affected the market and production of Peugeot vehicles in Nigeria. The PAN relies much on her three 2000MVA generators for production and day to day running of the company. Statistical average of previous years' electric load consumptions is used to forecast future load demand and plan for future budget requirements for production, electricity tariff and fuel requirement for power generation by budget planners in PAN which has led to wrong budget estimates. Forecasting electric load demand requires a suitable technique that will estimate the future Electric Demand load with high reliability and accuracy. PAN has to address this problem by generating electric power necessary to meet the power requirement for production processes and operations. Time series models are mathematical models that are used to model system behaviors that are represented by a sequence of observations and are very suitable in forecasting STLF such as weekly forecasting (Cheepati & Prasad, 2016). However, Computational Intelligence (CI) techniques such as Neural Networks (NNs), Evolutionary Programming (EP), Fuzzy Logic (FL), Genetic Algorithms (GA), Artificial Life (AL), Belief Networks (BN), Probabilistic Reasoning (PR) etc. and their hybrids can model complex systems due to their ability to approximate any non-linear system (Peter, Luhutyit, & Abdulkadir 2020). This paper seeks to predict monthly electric load demand of PAN by using Hybrid NARX- GA technique with a high degree of accuracy to enhance management decision and planning. The rest of the paper is organized as follows: Section 2 discusses the review of literature used in forecasting Electricity Load Demand Consumption. Section 3 discusses the methodology. Section 4 describes the system implementation and result evaluation of Hybrid NARX-GA models. In section 5, conclusion and the proposal of further research area is presented.

2. Review of Relevant Literatures

Forecasting electric load demand for any organization is a complex phenomenon due to the non-deterministic nature of the pattern of electricity consumption. Factors such as weather and economy affects the consumption of electricity, which has led to the development of several techniques in addressing the problem (Islam, Baharudin, Raza & Nallagownden, 2014). Several techniques are reviewed by considering the theoretical background, strength and weakness of each approach in other to justify the use of the current technique. Srivastava et al. (2016) states that the use of forecasted electric load demand in planning, budgets, production and maintenance is a vital function of management for decision making in a deregulated economy. Phuangpornpitak and Prommee (2016) posited that the forecasting model is a mathematical expression with independent variables which are inputs and dependent variable (forecasted value) of the system. According to Xing, Yang, Jiang, Wu, & Zhao (2016) load forecasting is divided into parametric and CI based techniques. The parametric techniques such as Time Series (TS), Multiple Linear Regression (MLR) techniques and Grey method (GM) are statistical approaches that define relationships between predictor variables and dependent variable suitable for modelling short time load demand (Adriana & Ardehali, 2014; Tuaimah & Abass, 2014; Cheepati & Prasad, 2016) while CI techniques are suitable for modelling short, medium and long term electric load demand. According to Bunnoon, Chalermyanontand Limsakul (2009) MLR technique is not suitable in forecasting medium term load demand. Tuaimah & Abass (2014) applied MLR for STLF at Iraqi power plant and obtained 71.9% MAPE. Auto-Regressive Moving Average (ARMA) is a statistical approach that uses linear relationships of variables in forecasting applications (Box, Jenkins, & Reinsel, 2016). The three component parts are: autoregressive, moving average and integrated processes. The autoregressive component is composed of the current and previous state that is integrated with the moving average component to predict the estimated future value. Srivastava et al. (2016) reported that generally ARIMA technique has the problem of inaccuracy in prediction and numerical uncertainty when applied in the forecasting of medium and long term electric load demand. According to Srivastava et al. (2016) ANN model outperforms ARIMA models when used alone due to its ability to model dynamic nonlinear systems effectively. Peter & Mubarak (2018) performed comparative analysis between ARIMA and ANN in forecasting rainfall and reported that ANN outperformed ARIMA in producing seasonal cyclical behaviour of rainfall with a lower value of MAPE. The State Space approach applies Kalman Filter to estimate load demand in combination with weather parameters. The Kalman Filter algorithm combines past state data set with noise to generate an estimate of unidentified variables recursively and its accuracy is a function of the gap between successive data points. Takeda, Tamura and Sato (2016) reported a 3.7% MAPE when Kalman Filter algorithm is used to estimate load consumption on weekly basis. Kalman Filter algorithm is not quite suitable in predicting medium and long term electric loads. Chen, Hong, Shen and Huang (2016) argued that the State Space approach describes a function to determine the nonlinearity factors that affect the system output.

Another set of approaches are those that utilised machine learning algorithm or soft computing, generally referred to as Computational Intelligence (CI) based approaches in Computer Science. The approaches are known to generate patterns from data sets and map systems that are not linear. According to Peter & Abdulkadir (2018) as reported in (Peter et al., 2020) CI approaches commonly uses numerical values in processing information, the techniques possess the potentials to tolerate errors, uncertainty, and imprecision; they can adapt to variations, identify patterns and reduce errors in data. The techniques commonly use the reasoning capacity embedded in them through learning in choosing features and performing estimation as output (Mateo et al., 2013).

FL as one of the CI technique uses the degree to which an element belongs to a set in making decisions (Peter & Tella, 2015). FL was used to estimate STLF and a result of 4.2% MAPE obtained (Pujar, 2010), however, it has been reported in (Badri, Ameli & Birjandi, 2012) that FL models generate results that are not accurate and are not stable numerically in comparison with ANN. ANN is an inspiration gotten from imitating the way human brain works in knowledge acquisition by using an electrical analogue of interconnected neurons and layers for approximating any nonlinear function (Peter, Abdulkadir, & Abdulhamid, 2017; Peter, Luhutyit, & Abdulkadir, 2020). It uses the concepts of supervised learning as well as unsupervised learning in its implementations. The robustness and computational capability has enable ANN to find applications in many forecasting areas. It can model dynamic and chaotic Electric Load Demand (ELD) situations due to its adaptation to situations. ANN model may generate an under-fitting or over-fitting of data if the training parameters are not correctly selected. In addressing the phenomena of under-fitting and over-fitting, the need to hybridized ANN with another algorithm with the potential of generating a global optimum solution. A better result with very low margins of error are obtained in forecasting when models are aggregated. This is due to their ability to complement each other's weaknesses (Patel & Sharma, 2018). GA is a global optimum search algorithm and hybridising it with ANN helps in addressing the problems of under-fitting and over-fitting that are easily associated with ANN. Neuro-Fuzzy approach was used in a STLF as stated in (Ekonomou, Christodoulou and Mladenov, 2016), however, FL is not a global search algorithm. Wavelet NN and FL are applied in the forecast of ELD and a MAPE of 1.31-2.08 are obtained as compared to Artificial Neuro-Fuzzy Inference System (ANFIS) and Radial Basis Function Neural Net (RBFNN) that yielded 2.78-3.32 and 2.10-3.84 respectively as reported in (Hanmandlu & Chauhan, 2011). A Neuro-GA generated about 2% improvement in MAPE when applied in STLF as reported in (Islam et al., 2014). In a MTLF reported in (Nezzar, Farah, Khadir & Chouireb, 2016) using the hybridization of X12- NAR-Feed Forward NN (FNN) a 2.35% MAPE value was obtained. The STLF reported in (Zhang, Xu, Dong, Meng, & Wong, 2013) showed an improvement in the application of hybrid approach. However, NARX aggregated with Back propagation algorithm gets trapped in local minima. GA avoids such difficulty due to its global search capabilities. This work leverage on this potential of GA to perform LTLF of ELD in PAN Ltd.

3. Methodology

In this section, design framework of the work is presented highlighting the steps taken to realize the forecasting model. The input variables identification and selection process, data collection and pre-processing techniques used in the research are presented. The Neural Network (NN) Architecture, the choice of network parameters, training algorithm optimization with Genetic algorithm, and the hybrid training algorithm used to train the network in modelling the system are presented. The performance metrics used in evaluating the model and the statistical forecasting metrics used in evaluating the model performance are also presented.

3.1 System Design

The work employed Ex-post facto design in developing the model. Figure 1 shows the system design framework for the research. The Input Variables Identification and Selection stage described how the independent variables were identified and selected. The Data Collection stage explains the source of the data and collection procedure. The reliability and validity of the instruments used in recording the data set are described in this stage. The Data Pre-processing stage described the technique used in normalizing the acquired data set required for NN training

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for optimal performance. The NN architecture design stage, describes the architecture, the network parameters and training algorithm used in the research. Justification was provided in this stage for the application of Genetic Algorithm in optimizing the network with Bayesian Regulation. The final stage of the design is the System Evaluation stage using the MAPE statistical metric to ascertain the model optimal performance.

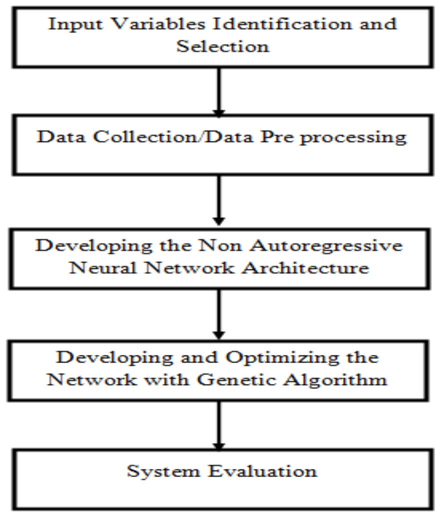

Figure 1: The System Design Framework

3.2 Identifying and Selecting the Input Variables

Statistical correlation technique and experience are employed in identifying the choice of appropriate input variables. The independent variables of the research are identified in the initial stage of the designed process which are extraneous variables that influenced the output of the system. The months, year, temperature, relative humidity, production, and electric load are the input variables used for the work.

3.3 Data Collection

The data for the forecasting model are obtained as secondary data. The group leader and head of utility of the maintenance department supplied the historical data for electricity load demand consumption from January 2000 to December 2017. And the corresponding production data are gotten from the office of the production manager of PAN Ltd. Average temperature and relative humidity are collected from NIMET office, Kaduna International Airport.

3.3.1 Instrument for Data Collection

The instrument is official power daily load demand in Mega Watts (MW) from control room VD24 11KV Switch Gear, and Switch Gear units in rooms A, B, and C are obtained for the research. The production shop floor for assembly shop chassis line gave the values of the production figures. Temperature and relative humidity historical records are gotten from the weather log books of NIMET office of Kaduna International Airport.

3.4 Input Variables Correlation

The Product Moment correlation is used in selecting the input variables due to its ease of implementation in MATLAB R2018a. Equation (1) is the mathematical expression of the Product Moment Correlation.

$$\rho_{XY} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y} \quad (1)$$

Where:

cov is the covariance

σ_X is the standard deviation of variable X

σ_Y is the standard deviation of variable Y

Table 1: Correlation between the Input Data Set

Input Variables	Correlation Coefficient
Temperature and Electric Load Demand	0.88
Relative Humidity and Electric Load Demand	0.40
Production and Electric Load Demand	0.54

3.4.1 Relationship between Temperature and Electric Load Demand

In Table 1, There is a strong correlation of 0.88 between the monthly temperature and monthly Electric Load Demand variables. This is because during dry season increase in temperature lead to increase demand for electricity for cooling purpose (more AC and fans are used) whereas, in Harmattan (Winter) season electricity is used for heating purposes while in Raining Season, there is a decrease in load consumption.

3.4.2 Relationship between Relative Humidity and Electric Load Demand

The relationship between the monthly Relative Humidity and monthly Electric Load Demand variables is a medium positive relationship of 0.40. This indicated a weak relationship between the Load and Humidity. Paint Shop production relies on humidity controls which have a direct relationship with the Electric Load Demand.

3.4.3 Relationship between Production and Electric Load Demand

In Table 1, the correlation coefficient of 0.54 is a medium relationship between Electric Load Demand and production. The number of vehicles produced determines the duration of time in which the production equipment is operational, which has a direct relationship with the energy demand. As the production increases hence the Electric Load Demands increases.

3.5 Data Set Partition

The Dataset was partitioned into Input Data and Target Datasets. The Input Dataset consist of 216X5 array of the month, Year, Average Temperature, Average Humidity and Production, while the Target Dataset is the Electric Load demand data set of 216X1 array. The data is partitioned for training, testing and validation using 10-fold cross validation partition scheme. Equation 2 is the cross validation estimate for the forecasting error of the fitted function f.

$$CV(f) = \frac{1}{N}\sum_{i=N}^{N} L(y_i, f^{-\kappa(i)}(x_i)) \quad (2)$$

Where:

$CV(f)$ is the Cross validation estimate of the prediction error of function f.

N is the data observations, $y_{i,}$ is the values $y_1, \ldots, y_{n,}$ $\kappa(i)$ is the indexing function, and $f^{-\kappa(i)}$ is the fitted function.

3.6 Data Pre-processing

Typographical discrepancies and inconsistencies in the data were removed from the Data obtained. The data set was then saved in the prescribed MATLAB format for Data scaling.

3.6.1 Data Normalization

The data was normalized to -1 to 1 scaling range by using the Max Min Data normalization scheme to enhance faster convergence during training. Equation 3 is the mathematical expression for Max Min Data normalization.

$$v' = \frac{v - A_{\min}}{A_{\max} - A_{\min}}\left(X_{upper\,bound} - X_{lower\,bounds}\right) - X_{lower\,bounds} \quad (3)$$

Where:

V' is the normalized data, v is the data to be normalized, A_{min} is the minimum value in the data to be normalized, A_{min} is the maximum value in the data to be normalized, $X_{upper\ bound}$ is the upper limit of the normalized data set, which is set to 1, and $X_{lower\ bound}$ is the lower limit of the normalized data set, which is set to -1.

3.7 Neural Network Architecture

In this work, the NN architecture is made up of three (3) parallel layered network comprising of the Input, Hidden and Output Layer with a feedback loop for multi-step ahead prediction as seen in Figure 2.

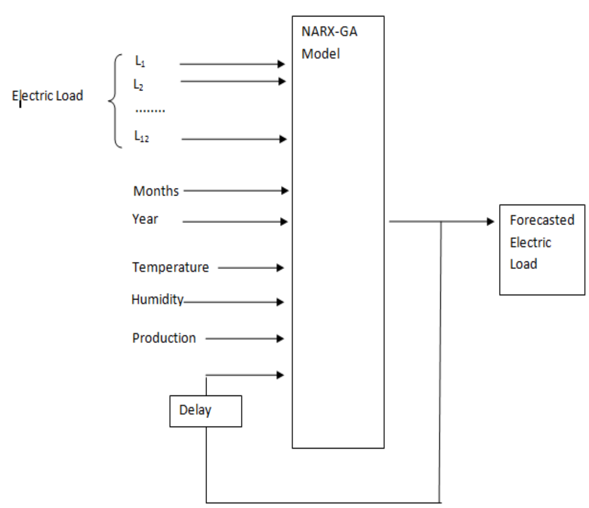

Figure 2: NARX Architecture for Forecasting

3.7.1 Input and Output Nodes

Five input neurons and one output neuron are used in designing the network. The number of input and output neurons must correspond to the number of input and output variables.

3.7.2 Hidden Neurons

The number of neuron are determined experimentally starting from one neuron in an incremental fashion. Three hidden neurons are final used for implementation of the network architecture.

3.7.3 Network Delay Parameters.

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The network delays parameters are determined by the Input –Target Cross correlation and Target autocorrelations. Equations 4 and 5 are the mathematical expression for estimating the Cross of two time series y_{1t} and y_2 respectively.

$$c_{y1y2}(k) = \frac{1}{T}\sum_{t=1}^{T-k}(y_{1t} - \bar{y}_1)(y_{2,t+k} - \bar{y}_2);\ k = 0,1,2,... \qquad (4)$$

Where: c_{y1y2} is the cross correlation between time series y_{1t} and $y_{2,t+k}$, $\bar{y}_1$ is the sample mean of time series y_{1t}

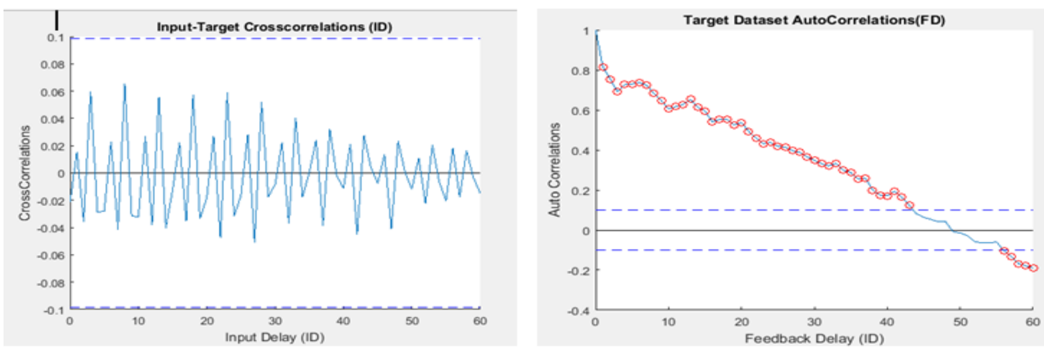
$\bar{y}_2$ are the sample means of the series $y_{2,t+k}$

$$\bar{\gamma}(h) = \frac{1}{n}\sum_{t=1}^{n-h}(x_{t+h} - \bar{x})(x_t - \bar{x}), \quad for - n < h < n \qquad (5)$$

Where: $\bar{\gamma}(h)$ is auto correlation of time series x_t, n is number of observations, h is lag, x_t is the time series, and

$\bar{x}$ is the mean of time series data.

$\bar{x}$



(a) Input-Target Cross Correlation

(b) Target Autocorrelations

Figure 3: Cross Correlation of the Input-Target Data Set

In figure 3a, high Cross Correlation value of 0.06 are obtained at about 5, 10,15,20,25 and 30 Input Delay. In figure 3b is the Auto Correlation of the Target Data set. High values of Correlations between 0.6 to 0.8 are obtained between the Feedback delay 1 to 10. The Delay of 1:5 is selected because of high cross correlation of 0.06 and a corresponding Auto correlation of 0.7. Since the Input DeLay and the Feedback Delay must correspond in NARX network, hence the choice of 1:5.

3.7.4 Selecting transfer function

In this work, the data normalization ranges from -1 to 1 and this conforms with the hyperbolic tangent transfer function, hence the choice of its usage in the hidden layer. Equation 6 is the mathematical expression of hyperbolic Tan function.

$$\tanh(n) = \frac{e^n - e^{-n}}{e^n + e^{-n}} \qquad (6)$$

Where: n is the number of inputs.

The default transfer function for NARX input and output layer configuration is the Purelin activation function which ranges from -1 to 1 as the hyperbolic Tan function. The inputs from the hidden layer neurons are mapped onto the Purelin activation function.

3.8 Training the Network

In training the Network, Bayesian Regularization (trainbr) algorithm was used due to its robust nature, requiring fewer number of cross validation time, and converges faster than many Back Propagation algorithms.

3.9 Generalization

In order to minimized overfitting of the training data set and effectively achieve good generalization, Bayesian Regularization algorithm was used for automated regularization of the NN.

3.10 Network Optimization by Genetic Algorithm

The network weight parameters are optimized by Genetic Algorithm (GA). The Input and Target data sets are fed as inputs variables into the GA. The input and the Target Dataset are used to compute the chromosomes length. The chromosomes are mapped to corresponding weights in the NN. An initial population and generations for the GA are generated. The GA operators used are “selection”, “crossover” and “mutation” for the creation of new population. The selection operator was applied to select the individuals (weights) to produce the next generation of offspring The population and generation are assigned the values of 100 and 200 respectively after several experimentations. The fitness function evaluated the fitness of each individual with the objective of minimizing the mean square error (MSE) of the network. The weights, biases vector, input and target data set are used as variables for the fitness function. The “selection tournament” function was used to pick each parent (weight) from a pool of weights, the best weights are picked randomly from the set of weights. In the tournament selection scheme, each candidate solution (the network weight) is selected at random based on its fitness value for recombination to form the next generation of offspring. The tournament selection technique is commonly used due to its robustness and ease of implementation. The crossover operator was used to recombine the parents (weights). This was done by selecting from each parent (weight) to take the value for a particular allele independent of its choices for other alleles. The “crossover heuristic” was used to combine the weights of parents by moving from worst parent to slightly past best parent. The final fitness value was evaluated until the best fitness value is obtained thereby terminating the network after optimization. The mutation operator applied random changes to individual parents (weights) in the network to form children (new weights). The Uniform multi-point mutation (mutation uniform) function was used.

3.11 Network Testing and Evaluation

In order to test and evaluate the best NN performance for the optimal model, a standard statistical forecasting metric Mean Absolute Percentage Error (MAPE) was used.

The MAPE forecasting evaluation parameter is defined mathematically as

$$MAPE = \frac{1}{n}\sum\frac{(X(t)-f(t))}{(X(t))}x100 \qquad (7)$$

Where: n is the sample size, $X(t)$ is the actual value, and $f(t)$ is the forecasted value.
MAPE is not affected by extreme deviations and is commonly used for Load forecasting applications.

4. System Implementation and Results

This section presents the model, experimental setup and the results obtained from the evaluation of the model base on the performance metric of MAPE.

4.1 The Model

Figure 4 shows the architecture of the NARX network model used to forecast the monthly Electric Load for the period of one year. The model has five inputs, 1:5 delay and one output with a corresponding feedback loop.

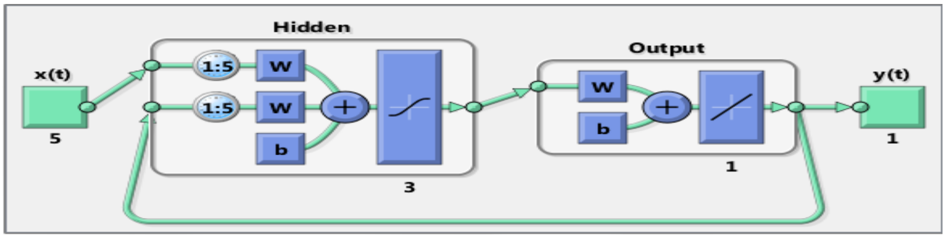


Figure 4: NARX Neural Network Closed loop view

4.2 Hardware and Software experimental setup

The developed NARX-GA network model was implemented on HP laptop with MATLAB R2018a software, running on Windows7 Ultimate 24-bit OS. The processor is a Pentium ® Dual – Core CPU T4300 @ 2.10GHz. RAM size is 4.00GB for developing, testing and simulating the design.

4.3 Model Training, Testing, Predicted Results and Discussions

Figure 5 shows the training and Test curves. The Best training performance was at 2517.0598 at 154 epochs. Figure 5 shows well fitted curves to the best line of fit for both the training and testing.

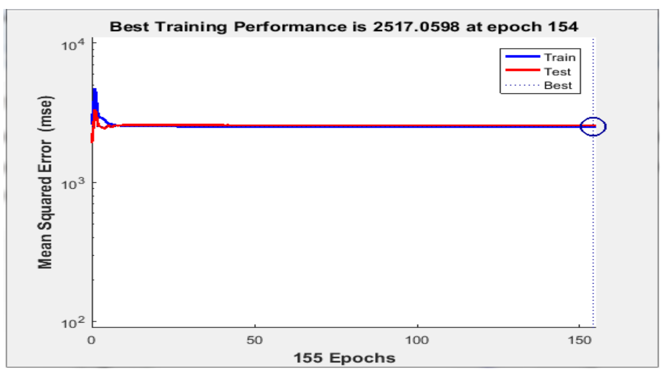


Figure 5: Training Performance Plot of the Model

Figure 6 is the genetic algorithm plot in the first subplot showing how the algorithm achieves best fit at about the 15 generation up to the 100 generation with a value of 1.24124 and a mean of 1.26889. The fitness is quite remarkable. The number of function evaluations was at 20200. The second subplot in Figure 6 shows the graph of the Forecasted Electric Load Demand Vs. months.

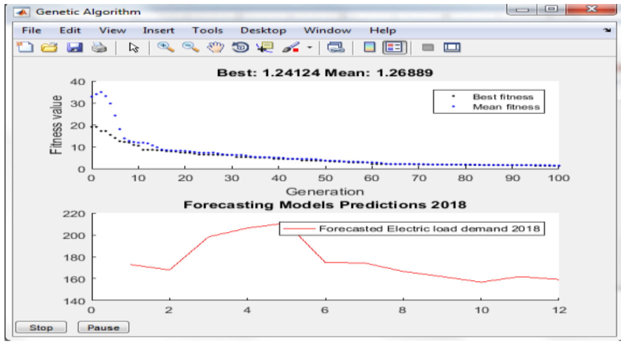


Figure 6: Genetic Algorithm Displaying the Fitness Values and

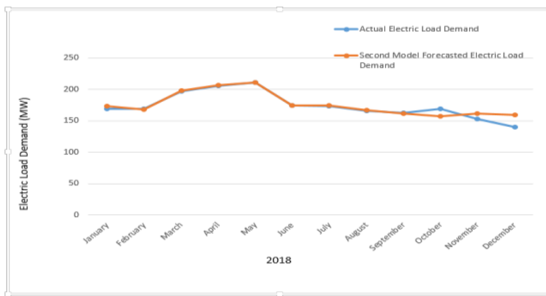


Figure 7: The Forecasted and Actual Electric Load for year 2018

Figure 7 shows the plot of the model output and the actual electric load demand for January to December 2018.The forecast for January 2018 was 172.8 MW while the actual Electric Load Demand was 168.87 MW. This shows a deviation of 15.1 MW indicating a forecast error of 2.3%. High deviations of 1.1, 2.7 and 4.8 were observed between the forecasted and actual Electric Load Demands in October, November and December with forecast error of 0.7%, 1.7%, and 3.1% respectively. The deviations between the forecasted and actual Electric Load Demand are due to other exogenous independent variables that influences Electric Load Demand such as Gross Domestic Product, Consumer Pricing Index and other un-deterministic management decisions such as load shedding and factory closure for shutdown maintenance which has a relationship with car production and sales. The Electric Load Demand in January and February are relatively low compared to March, this is because the ambient temperature is low and most office air conditioning units are not being used during the Harmattan Season. The high Electric Load Demand in March, April, and May is due to high ambient temperature during the Heat season requiring the use industrial fans, Cooling Towers and office Air conditioning units thereby resulting to high energy consumption during these months. The Electric Load Demands is lower in June, July and August due to the low ambient temperatures as a result of constant rainfall during these months resulting in lower energy demands in the offices and for production.

5. Conclusion

This research has shown the potential of hybrid Non-linear Auto-Regressive Neural Network with Exogenous Inputs (NARX) and Genetic Algorithm (GA) in forecasting Electric Load Demand of PAN Ltd. The model was developed based on some selected input variables from the historical dataset of Electric Load Demand, temperature, relative humidity and production. It achieved a

MAPE of 0.56%, which shows the potential efficacy of hybrid machine learning with evolutionary algorithm as a good forecasting tool. The implications of this study is that Utility industries needs to apply machine learning tools in forecasting Energy demands for day to day operations and for planning purpose. The forecasting techniques used by Utility industries and companies needs re-evaluation in unit containment, load shedding, annual shutdown maintenance and budget preparations through the use of machine learning forecasting techniques. The result of this study is in line with Zou, Xia, Yang and Wang (2007) confirms the ability of hybrid machine learning algorithm in modeling complex dynamic non-linear time series systems.

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