Predicting Electricity Consumption Using Radial Basis Function (RBF) Network

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***Abstract*-The management of the demand and supply pattern of electrical energy in Nigeria is a complex task that requires highly informative approaches; these approaches should be able to provide adequate models for predicting the future utilization of the energy in order to boost the economy of the nation. This study applied an Artificial Neural Network-based model, often called Radial Basis Function (RBF) network to time-series prediction of electricity consumption in Nigerian using historical data gathered from CBN annual bulletins. The implementation of the model was carried out using Neural Network Tool *(nntool)* of the MATLAB 7.6.0 (R2008a) tool box. The study showed that RBF network performs better than its equivalent Backpropagation (BP) networks that were compared with it.**

Keyword- Prediction; Radial Basis Function (RBF) Network; MATLAB; Electricity Consumption; Nigeria

I. INTRODUCTION

Economic growth and development has been the main pillar upon which every highly industrialized country is pivots, and one of the means to attain such growth is uninterrupted electric power supply. Electricity is the most flexible form of energy and constitutes one of the critical resources for modern life and economic growth of any nation [1].

In Nigeria, electricity is one of the oldest forms of energy available for daily activities. It is also, unfortunately, grossly inadequate to meet the demand of an ever increasing population. This is largely due to inadequate planning [2]. Arimah [3] gave an overview of the present situation of the Nigerian electricity industry when he wrote,

"…the Nigeria electricity industry is bedeviled with many serious technical, managerial, personnel, financial and logistic problems. Furthermore, the demand for electricity has continued to outstrip capacity; the end-result has been the delivery of poor and shoddy services, evidenced by frequent power failure…"

As can be deduced from the above statements, the whole scenario lies on the absence of more informative and detailed data on time-series bases for electricity consumption.

Time-series prediction concentrates on building models of the process using available knowledge and information. The constructed models can then be used to simulate future events of the process [4].

In science, technology and economy, there are many interesting processes and phenomena, whose predictions are very useful and profitable. Examples of such phenomena include electricity demand and supply. Electricity demand forecasts are required by companies who need to predict their customers' demands, and by those wishing to trade electricity as a commodity on financial markets.

Various approaches to time-series prediction of electricity consumption have been studied and reported in researches over the years. Prediction infers the future states of multiple variables based on historical states of those variables [5]. Most of these approaches or methods are statistical and/or artificial neural networks (ANNs) based. Statistical methods are usually linear regression models. Notables among them are autoregressive (AR) models, linear regression (LR) method and autoregressive moving average (ARMA) models, which have been the most used methods in the western world in the 1920's [6, 7].

ANN methods are nonlinear in nature. They are biologically inspired models that typically consist of simple computing units connected in a certain manner [4, 8]. Structure of the connections between units and the calculation that a unit performs vary in different neural models. Characteristic of neural networks is that the optimization of all the model parameters is carried out at the same time with a learning algorithm. Grando et al., [5] noted that, the advantages of ANNs for predicting time-series phenomena are that knowledge of the internal structure is not necessarily needed, arbitrary nonlinear prediction could be learned, and additionally, some past observations could be integrated in the prediction. In recent years, ANN models have enjoyed greater patronage of researchers. They have been applied to solving national problems involving prediction. For example, in Nigeria, ANNs have been applied to stock performance prediction in the capital market, population prediction, weather forecasting, bankrupt prediction, student academic performance prediction, fuel consumption forecast, and desert dust prediction in the atmosphere [9-12].

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Typical neural networks such as multilayer perceptron (MLP) and radial basis function (RBF) have been proved to be universal function approximators [13]. This gives ANNs certain attractiveness in time-series modeling [4, 14-16]. One major disadvantage of ANN models is that their structures are not very suitable to represent temporal patterns [5, 8]. Regardless of the nature of their linearity, all methods try to build a model of a process that is to be predicted. These models connect the last values of the series to their future values.

In this paper, radial basis function (RBF) network is applied to predicting electricity consumption in Nigeria using historical data from Central Bank of Nigeria (CBN) website. The performance of RBF network is analyzed and compared with two types of Backpropagation (BP) networks (i.e., Feed-forward and Elman) labeled MLP1 and MLP2 respectively. Their sums of square errors (SSE) were computed in order to determine the level of accuracy, efficiency and reliability of RBF neural network. All the networks are simulated using Neural Network Tool (nntool) of MATLAB 7.6.0. (R2008a) software.

II. LITERATURE SURVEY

Over the last few decades, a number of prediction methods have been developed. These methods are mainly statistical or artificial intelligence methods. Statistical approaches usually require a mathematical model that represents consumption pattern as function of different factors such as time, weather, and customer classes whereas human thinking, learning and reasoning method is used for energy consumption in artificial intelligence methods [17]. Statistical and artificial intelligence (AI) methods each includes several methods discussed below.

Ma et al., [18] integrated multiple linear regression and self-regression methods to predict monthly power energy consumption of large-scale public buildings. In the work of Cho et al., [19] the regression model was developed on 1-day, 1-week, and 3-month measurements, leading to prediction errors in the annual energy consumption of 100%, 30%, 6% respectively. These results show that the length of the measurement period strongly influences the temperature-dependent regression models.

Mohamed and Bodger [20] proposed a multiple linear regression model using GDP, electricity price and population as selected variables deemed most relevant for electricity consumption in New Zealand. The result showed the forecast was very comparable with the national forecast with accuracy of 89%. Kimbara et al. [21] developed an Auto-Regressive Integrated Moving Average (ARIMA) model to implement on-line prediction. The model was first derived from the past load, and then used to predict load profiles for the next day. ARIMA with external inputs (ARIMAX) model has also been applied to some applications, predicting the power demands of buildings [22]. Ghaderi et al., [23] estimated electricity demand function for 17 groups of industries in Iran, using a Log-Linear Auto-Regression Model and annual time-series data from 1980 to 2002. The estimation results indicated the weak sensitivity of industrial energy consumption to price change which is the principal independent factor among the number of economic variables. As can be seen from the cited works above, statistical methods require large amount of information relevant to appliances, customers, economics etc., which may not be readily available. In other words, the outcomes of their predictions may be dependent on some unknown variables, whose effects on the process cannot be estimated and usually contain noise that cannot be cancelled out. According to Sarlak et al. [17], statistical methods do not produce satisfactory results when used to estimate electrical energy consumption, because their effectual factors are strongly nonlinear and complicated.

AI techniques, such as artificial neural network (ANN), fuzzy logic and genetic algorithms (GA), have been used to improve the accuracy and reliability of chaotic process prediction. Specifically, ANN has been applied to load forecast, energy consumption forecast, capital market stock performance prediction, students' academic performance estimation, population prediction and so on. In the area of electricity usage, early studies have successfully used neural networks for modelling the time-series of electricity consumption. Nizami and Al-Garni [24] proposed a simple feed-forward neural network to relate the electric energy consumption to the number of occupancy and weather data. Gonzalez and Zamarreno [25] predicted short-time electricity load with a special neural network that feeds back part of its output. Azadeh et al. [26] predicted the long-term annual electricity consumption in energy intensive manufacturing industries, and showed that the neural network is very applicable to such problem when energy consumption shows high fluctuation. Sarlak et al. [17] proposed Back propagation (BP) network for enhancing the accuracy of daily and hourly short-time load forecast for Iran using the country's power consumption data for the years 1994 through 2005.

Most of the early studies discussed above, proposed multilayer perceptron (MLP). However, other ANN models are beginning to attract attentions. Lendasse et al. [27] applied Self-Organizing Maps (SOM) to the estimation of electricity consumption of Poland and compared the results with those of other linear and nonlinear models. The result showed that SOM produced the best model. Grando et al. [5] developed a prediction model based on the principle of Liquid State Machine (LSM) for forecasting the electric energy demand in state Rio Grande do Sul (Brazil) using historical data over the period of ten years (1998-2008). The MSE of the system was found to be (0.00001).

ANNs develop solution fast and have less reliance on domain experience. ANNs develop solution to any problem under the consideration that one may not get thorough understanding of the subject matter. Since the country Nigeria is statistically underdeveloped compared with some advanced countries in the world, using ANNs may contribute significantly to the

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improvement of accuracy of electric consumption forecasting for the country. The application of Radial Basis Function (RBF) network to the approximation of stochastic and chaotic processes has also been reported in researches.

III. METHOD: RADIAL BASIS FUNCTION (RBF) NETWORK

Radial basis functions (RBF) is an important tool in solving problems involving time-series approximation and in pattern classification. An RBF network is an artificial neural network that uses radial basis functions as activation functions. It is a linear combination of radial basis functions pattern recognition and control. Wu and Liu [12] asserted that RBF neural networks could be used to estimate any continuous function mapping with a reasonable level of accuracy. Fig. 1 shows an RBF neural network. The network consists of three different layers: input layer, hidden layer and output layer. The bell shaped curves in the hidden nodes indicate that each node in the hidden layer represents a radial basis function that is centered on a vector in the feature space. First, the input signals (xi) composing an input vector is sent to a hidden layer composed of RBF neural units. The second layer is the output layer, and the transfer functions of the neurons are linear units. Connections between the input and hidden layers have unit weights. The hidden layer of an RBF network has several forms of radial basis activation function. The hidden layer performs a non-linear transformation of the input space, resulting in hidden space of typically higher dimensionality than that of the input space, whereas the output layer performs linear regression to predict the desired targets [8].

The input vector is fed to the jth hidden node where it is put through that node's radial basis activation function defined below.

$$\propto_j = f(x_i) = exp\left[\frac{-\|x - c_j\|^2}{2\sigma j^2}\right] \tag{1}$$

where $\|X - c_j\|$ is the distance between the feature vector x and the center vector c_j of that radial basis function. The values of α_j are the outputs of the radial basis functions. These radial basis functions are on a two-dimensional feature space. The value of $\|X - c_j\|$ can be determined by Eq. (2).

$$\|x - c_j\| = \sqrt{\sum_{i=1}^{m}(x_i - c_{ij})}, i = 1, 2, \dots, m \tag{2}$$

where $X = [x_1, x_2, \dots, x_m]^T$

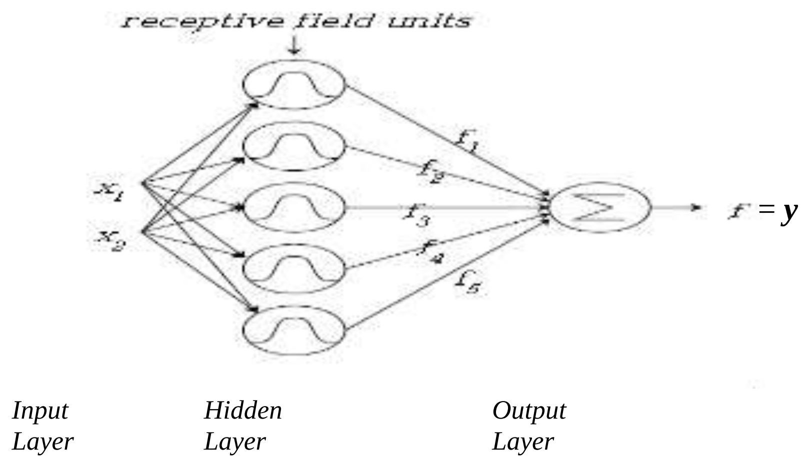

Fig. 1 RBF neural network architecture

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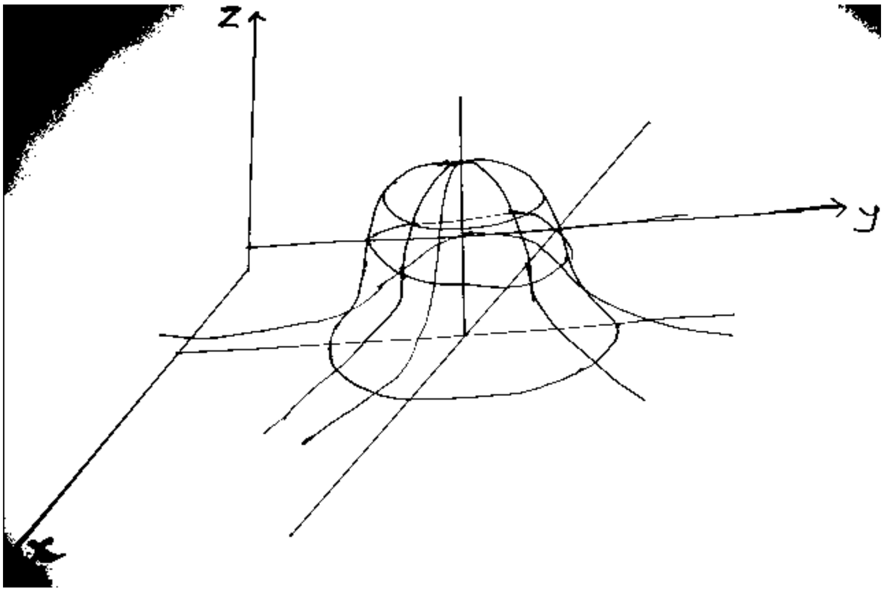

Fig. 2 Two-dimensional feature space of RBF

As can be deduced from Fig. 2, (α_j) equidistant from the center in all directions have the same values. It is why these are called radial basis function. The network output y is shaped by a linearly weighted sum of the number of basis functions in the hidden layer. The values of the output nodes can be defined as:

$$y_k = \sum_{j=1}^{n} w_{jk} \propto_j \tag{3}$$

where y_k , the kth component of y , is the output of the kth node in the output layer, w_{jk} is the weight from neuron of the jth hidden layer to neuron of the kth output layer, and α_j is the output of the jth node of the hidden layer. With the described structure, the hidden layer consists of j hidden nodes, which use nonlinear transformations to the input space. However, the output of the network is a linear combination of the basis functions computed by the hidden nodes [12].

A. *Training the RBF Network*

Training the RBF network is in two stages, regarded by Haykin [8] as hybrid training. The ultimate goal of these stages involves determining the number of RBF units, with width of RBF units and the output layer weight values in order to minimized the sum of square error (SSE), which expressed by Wu and Liu [12] as:

$$SSE = \frac{1}{2}\sum_{i=1}^{N}\sum_{k}\left\{t_k^i - y_k^i(x^i)\right\}^2 \tag{4}$$

where t_k^i are the target values, $y_k^i(x^i)$ is the network output from input vector x^i, and *N* is the number of training samples. The SSE can be minimized by adjusting the parameter w_{jk} (shown in Eq. (3)) in a manner similar to that of Backpropagation (BP) network. There is only one set of parameters instead of two as was the case for BP networks. Upon suppressing the index *q* (i.e., feature vectors/ target vector), SSE, simply represented as *E*, obtained as:

$$E = \frac{1}{k}\sum_{i=1}^{k}(t_k - y_k)^2 \tag{5}$$

$$E = \frac{1}{k}\sum_{i=1}^{k}\left(t - \frac{1}{J}\sum w_{jk} \propto_j\right)^2 \tag{6}$$

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Differentiating E with respect to w_{jk} yield

$$\frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial y_k} \cdot \frac{\partial y_k}{\partial w_{jk}} = \left[-\frac{2}{J} \sum_{i=1}^{J} (t_k - y_k) \right] \cdot \left(\frac{\propto_j}{J} \right) \tag{7}$$

Substituting this into the steepest descent method, and

$$w_{jk}^{(n+1)} = w_{jk}^{(n)} + \left[\frac{2\eta}{JK} \sum_{i=1}^{J} (t_k - y_k) \right] \propto_j \tag{8}$$

where η is the learning rate, upon training the network over all Q feature vector, Eq. (8) becomes:

$$w_{jk}^{(n+1)} = w_{jk}^{(n)} + \left[\frac{2\eta}{JK} \sum_{q=1}^{Q} \sum_{i=1}^{J} (t_k - y_k) \right] . \propto_j^Q \tag{9}$$

There are still missing information before an algorithm can be implemented for training an RBF network on a given data set $\{\{x^{(q)}: q=1, \ldots, Q\}, \{t^{(q)}: q=1, \ldots, Q\}\}$. Here the feature vectors for training (the exemplar vectors) are paired with the target vector by the index q. Yet the center vectors $\{c^{(m)}: m=1\ldots, M\}$ on which to center the radial basis function is still unknown. M and the spread parameter σ also remain unknown. There are different methods to get such information. The original method is to use exemplar vectors $\{x^{(q)}: q=1,\ldots, Q\}$ as the centers by putting $c^{(m)}=x^{(q)}$ for m=1, …, Q. This is satisfactory when the exemplar feature vectors are scattered well over the feature space, which means they must be numerous and cover all possible classes.

B. A Simple Algorithm for Training RBF Network

To implement the Eq. (9) above, a seven-steps algorithm is proposed below.

Step1: Read the data file to get *N, J, K*, and *Q*, the feature vectors and their target vector, input the number of iterations I, set

i=0, set *Q* centers of RBF's as the *Q* exemplar vectors, let *J=2Q*.

Step2: Find the average distance between centers, eliminate the centers too close to another, set J as final set of centers,

compute σ, and draw the parameters $\{w_{jk}\}$ randomly between -0.5 and 0.5

Step3: Compute $\propto_j$ and y_k, and then *E*.

Step4: Update all parameters w_{jk} for all j and k at the current iteration by *Eq. (9)*.

Step5: Repeat *step3* to compute the new value for *E*.

Step6: If new *E* is smaller than the old *E*, then increase it else decrease it.

Step7: Increment iteration *I*, if *i<I*, then goto *step4* else end.

IV. IMPLEMENTATION SETUP

Fig. 3 contains historical data used to train the built RBF network model, with time series of 26 years (1964-1989) and data size of 208. 65% (135) of the dataset was used for the training, 15% (31) for validation while the remaining 20% (42) was used for testing. The same dataset was used to train other two Backpropagation models (Feed-forward and Elman Backpropagation) for the same number of epoch (1000), determining which model returned the minimum sum of square errors (SSE). All the training and implementations of the models were carried out on a laptop with the following configuration: Processor speed of 1.66GHz, RAM of 2GB, HDD of 140GB and a 32-bit operating system. Software used were MS-Excel 2007 for hosting historical data, Windows 7 as operating system and MATLABTM 7.6.0 (R2008a) for designing, training and testing the neural network models. The RBF network model constructed is shown in Fig. 4.

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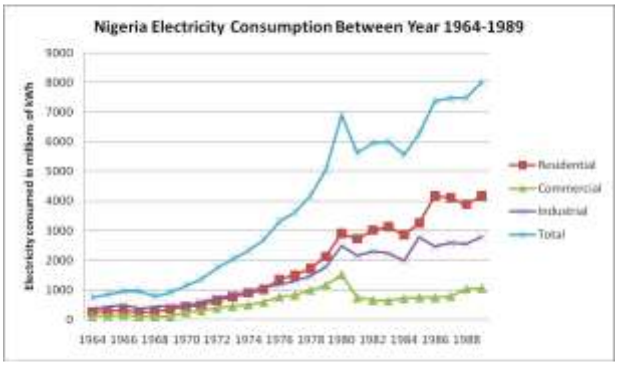

Fig.3 Electricity consumption pattern in Nigeria

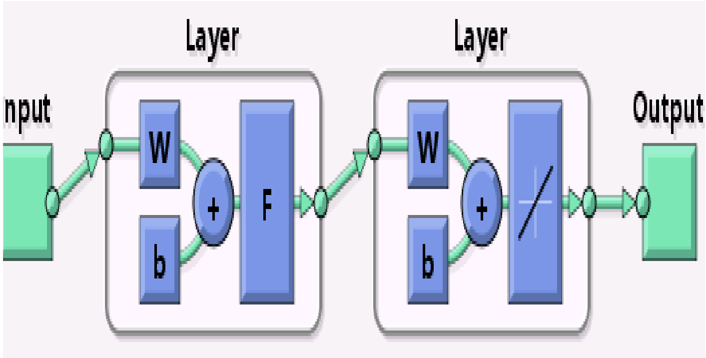

Fig. 4 RBF network model (exact fit)

A. Parameters for Performance Evaluation

In this work, the measures used to evaluate prediction accuracy of RBF network and other two Backpropagation networks are Sum of Square Error (SSE) and Correlation Coefficient (r) where $-1 \leq r \leq 1$ when prediction is perfect, r=1. The purpose of calculating r is to determine if there exist any positive relationship between the target and the output simulated by the models.

V. RESULTS AND DISCUSSION

The input to all models and the output calculated for existing data are given in TABLE 1. All the three models are constructed using the same input dataset. After the models have been constructed and validated, electricity consumption of the previous years is simulated using these models. The data in the table are also graphically represented in Fig. 5. All the network models maintain a topology of 3-10-1 i.e., each contains 3 neurons in the input layer, 10 neurons in the hidden layer and only 1 neuron in the output layer. The entire process of designing a network, training it, optimizing its performance entail process of considerable trials and error because no foolproof rules exist for selecting the numbers of neurons in the hidden layer or the numbers of hidden layers [8, 28]. In each of the network simulated, residential consumption, commercial consumption and industrial consumption of electricity served as inputs while total consumption served as target output.

TABLE 1 TARGET OUTPUT AND OUTPUTS FROM MLP AND RBF NEURAL NETWORK (MILLION KWH)

Year	Target Output	Output of Backpropagation Feed-Forward (MLP1)	Square Error	Output of Backpropagation Elman (MLP2)	Square Error	Output of RBF	Square Error
1964	752	962.0837	0.0780457	752.7408	0.0000010	750.0014	0.0000071
1965	847	965.3129	0.0195118	752.4513	0.0124608	846.0001	0.0000014
1966	955	952.4229	0.0000073	752.0641	0.0451555	955.0000	0.0000000
1967	955	945.9133	0.0000905	752.6400	0.0448996	955.0001	0.0000000
1968	793	941.8295	0.0352234	752.5889	0.0025969	790.0003	0.0000143
1969	923	996.9764	0.0064237	752.5054	0.0341207	923.0100	0.0000000
1970	1147	1555.6767	0.1269501	837.5810	0.0727725	1147.0010	0.0000000
1971	1366	1612.4066	0.0325389	764.7711	0.1937217	1366.0000	0.0000000
1972	1754	1991.5114	0.0183362	905.4188	0.2340602	1754.0000	0.0000000
1973	2045	2151.3100	0.0027025	1007.4872	0.2573951	2045.0000	0.0000000
1974	2332	2327.8683	0.0000031	1171.4635	0.2476627	2332.0000	0.0000000
1975	2707	2707.9539	0.0000001	2267.9937	0.0263006	2707.0500	0.0000000
1976	3317	3787.7368	0.0201403	4330.3238	0.0933266	3317.0000	0.0000000
1977	3617	3910.5501	0.0065867	2845.7681	0.0454646	3616.9990	0.0000000
1978	4178	4179.5856	0.0000001	752.0001	0.6724157	4178.2000	0.0000000
1979	5066	4967.3151	0.0003795	752.0000	0.7251534	5066.1120	0.0000000
1980	6899	6418.2186	0.0048565	752.0000	0.7938787	6898.0000	0.0000000
1981	5621	5476.7021	0.0006590	752.0000	0.7503301	5621.0006	0.0000000
1982	5970	5694.4270	0.0021307	752.0000	0.7639404	5970.1000	0.0000000
1983	6000	5625.8150	0.0038893	752.0000	0.7650418	6000.0010	0.0000000
1984	5568	5364.2049	0.0013396	752.0000	0.7481256	5569.0011	0.0000000
1985	6285	7312.3110	0.0267173	752.0000	0.7750162	6284.6700	0.0000000
1986	7375	7076.5203	0.0016380	752.0000	0.8064649	7375.0000	0.0000000
1987	7471	7198.4598	0.0013308	752.0000	0.8088199	7471.0000	0.0000000
1988	7475	7448.0097	0.0000130	752.0000	0.8089168	7474.9900	0.0000000
1989	8019	7608.1093	0.0026255	752.0000	0.8212396	8019.0011	0.0000000

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In each case, the square error is calculated by

$$Square\ Error = \left[\frac{Target\ Output - Network\ Output}{Target\ Output}\right]^2$$

In Fig.5, it can be observed that the outputs given by RBF model are very comparable with the target output, the MLP1 outputs are somewhat comparable to the target, and MLP2 outputs are not. This implies that both, RBF network and MLP1 are efficient at minimizing the performance criterion (sum-of-square error (SSE)) shown in TABLE 2. As shown the graph (Fig.5), the performance of MLP2 increases during 1964 to 1976, and drastically decreases until it comes to a halt in 1978. From the SSE values and correlation coefficient (r) given in TABLE 2, it can be proved that RBF network has shown a very powerful function approximation, thereby outperforms the other two equivalent Backpropagation models (MLP1 & MLP2). Thus, RBF neural network provides a better model for solving problems involving time-series approximation and pattern classification. According to TABLE 2, only MLP2 shows a very high SSE value (10.5492814) and negative correlation coefficient (r=-0.104825251) whereas MLP1 and RBF network both show highly positive correlation coefficient with values of r equal to 0.993135006 and 0.999999960 respectively. The implication of this is that unlike MLP1 and RBF network, there exists poor/no relationship between the electricity consumption output simulated by MLP2 with the target consumption values. In terms of SSE values, RBF network outperforms MLP1 and MLP2 with the least possible value of 0.00002283.

TABLE 2 SSE VALUES AND CORRELATION COEFFICIENT OF THE THREE APPROACHES

Approach	**SSE Values**	**R**
Feed-forward Backpropagation (MLP1)	0.39213972	0.993135006
Elman Backpropagation (MLP2)	10.5492814	-0.104825251
Radial Basis Function (RBF)	0.00002283	0.999999960

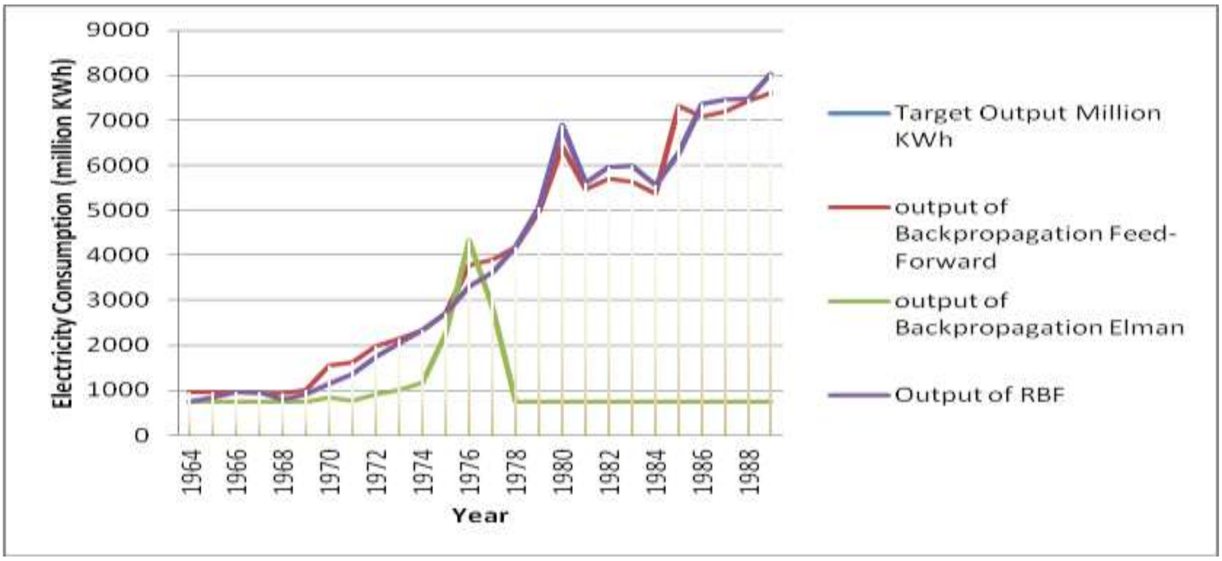

Fig. 5 Comparison of target output and outputs produced by the three models (KWh)

Forecasts for the next few years from the three models are given in TABLE 3. The prediction using RBF network model has 99.8% prediction bounds. Forecasts are determined by providing new dataset that was not used during the training session to the constructed models and comparing their outputs with the expected output (million kWh) in terms of percentage accuracy.

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TABLE 3 ELECTRICITY CONSUMPTION FORECAST INTO FUTURE DISTANCE

Year	**Expected Output**	**Feed-Forward Backpropagation (MPL1)**	**Percentage Accuracy**	**Elman Backpropagation (MLP2)**	**Percentage Accuracy**	**Radial Basis Function (RBF) Network**	**Percentage Accuracy**
2000	13720	12716.1043	92.68	11297.3760	82.34	12920.9904	94.18
2001	17370	17010.2726	97.93	14655.3658	84.37	17310.0000	99.65
2002	14770	13187.0658	89.28	10292.8778	69.69	14068.0012	95.25
2003	14550	12056.1026	82.86	10043.2760	69.03	14350.0000	98.63
2004	14550	11285.9613	77.57	10255.3961	70.48	13550.0000	93.13
2005	18430	14345.9306	77.84	12155.1334	65.95	18130.0092	98.37
2006	14460	13858.0625	95.84	12562.2533	86.88	14250.2220	98.55
2007	17710	16945.5586	95.68	13262.0397	74.88	17600.0095	99.38
2008	15850	12380.0670	78.11	13258.2952	83.65	15650.0000	98.74
2009	15850	14935.5673	94.23	14300.2457	90.22	14850.0000	93.69
2010	19210	15543.2144	80.91	15107.0263	78.64	18110.0000	94.27
2011	19210	13087.1224	68.13	14263.2148	74.25	18219.9763	94.85
2015	22570	17924.8412	79.42	17152.7018	76.00	22120.0001	98.01
2020	27340	17321.2724	63.36	15921.4115	58.23	26340.0023	96.34
2025	33460	24684.0988	73.77	15300.7020	45.73	33340.9321	99.64
2030	37590	20121.4554	53.53	19198.5134	51.07	37520.5352	99.82

VI. CONCLUSIONS AND FUTURE WORKS

The results obtained from the study actually showed that RBF networks are capable of predicting or forecasting electricity consumption with high-level precision than its equivalent Backpropagation (BP) networks, evident from the computed SSE values and Correlation Coefficient values. Although, the performance of feed-forward Backpropagation network (MLP1) is quite appreciable, it is not as efficient as RBF neural network. The experiment confirmed that a RBF network demonstrated a very powerful performance in function approximation and estimation properties. From TABLE 3, the percent accuracy of MLP1 ranges from 53.33% to 97.93%; that of MLP2 ranges from 45.73% to 90.22% while the percentage accuracy of RBF network ranges from 93.13% to 99.82%. Electric power development of any nation provides an incentive to economic and industrial activities, and as well foster rapid development in both rural and urban communities. The results of this research can be used to formulate policy on the consumption of electric energy by the Federal Government and the stakeholders in the power sector. The results can also serve as reference guide and information source to power distribution centers of the Power Holding Company of Nigeria (PHCN) to predict customers' demands of electricity in order to bridge the gaps between the expected and distributed quantities. Further research can be directed towards comparing the predicted results of electricity consumption using the proposed RBF network with those of any other sophisticated techniques like self-organizing map (SOM), liquid state machine (LSM), support vector machine (SVM), case-base reasoning (CBR), neuro-fuzzy predictor, and using statistical tools to verify if there exists a significant difference between the outcomes.

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