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ELECTRICITY CONSUMPTION PREDICTION SYSTEM USING A RADIAL BASIS FUNCTION NEURAL NETWORK

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ABSTRACT

The observed poor quality of service being experienced in the power sector of Nigeria economy has been traced to non-availability of adequate model that can handle the inconsistencies associated with traditional statistical models for predicting consumers' electricity need, so as to bridge the gap between the demand and supply of the energy. This research presents Electricity Consumption Prediction System (ECPS) based on the principle of radial basis function neural network to predict the country's electricity consumption using the historical data sourced from Central Bank of Nigeria (CBN) annual statistical bulletin. The entire datasets used in the study were divided into train, validation and test sets in the ratio of 13:3:4. By the above, 65% of the entire data were used for the training, 15% for validation and 20% for testing. The train data was presented to the constructed models to approximate the function that maps the input patterns to some known target values. The models were also used to simulate both validation and the test datasets as case data on the consistency of results obtained from the training session through the train data. Experimental results showed that RBF network model performs better than equivalent Backpropagation (BP) network models that were compared with it and provides the best platform for developing a forecast system.

Keywords: Electricity, Forecast, Radial Basis Function (RBF) network, ECPS, Backpropagation

INTRODUCTION

Adequate power supply is an unavoidable requirement to national growth and development because electricity generation, transmission and distribution are capital-intensive activities requiring enormous resources such as funds, capacity and intellectual capabilities. In the prevailing circumstances in Nigeria where funds available are progressively declining, creative and innovative solutions are necessary to tackle the power supply problem (Sambo et al., 2007). The former President Umaru Musa Yar'adua has already unveiled a mission, setting an agenda of industrializing Nigeria, by 2020 which is also an integral part of the present administration's agenda. For this mission to be realized, electricity sector must be accorded paramount priority.

To ensure adequate planning and management of electricity demand and supply in the nation, energy analysis should be an integral exercise of the stakeholders and the government, particularly, Energy Commission of Nigeria (ECN), Nigeria Electricity Regulatory Commission (NERC) and Power Holding Company of Nigeria (PHCN). There is therefore, the need to device an efficient mechanism, technique or tool for forecasting future utilization of this energy by different classes of consumers, with high level of prediction accuracy, as part of its planning process. The present situation in the Nigeria electricity sector is pathetic. Unfortunately, our electricity supply is grossly inadequate to meet the demand of an ever increasing population (Ubani, Umeh & Ugwu, 2013).

Most of the traditional approaches to the time-series prediction of electricity consumption are statistical methods such as linear regression (LR), analysis of variance (ANOVA), autoregression (AR) and autoregressive moving average (ARMA) which have been applied to electricity consumption forecast by several researchers over the years. The major limitations to these traditional approaches are, they are not very suitable for modelling the time-series of stochastic and chaotic systems such as electricity consumption because they are very sensitive to changes in the initial conditions (measurements at the starting time); they make assumptions which are sometimes found unrealistic; and they rely heavily on several factors whose information may not be readily available and as well, time-consuming.

Introduction of Artificial Neural Network (ANN) has immensely empowered the forecasting techniques of complex systems since the last few decades. Such system could include electric load forecast, atmospheric weather conditions, stock performance in the capital market, students' academic performance, network traffic etc. ANNs are helpful in the situation where underlying processes may display chaotic properties, because they do not require prior knowledge of the system under consideration and are suitable to model dynamic systems on real-time basis. The most popular ANN model for time-series prediction is back propagation networks. In the area of electricity usage forecast, early studies have successfully used the same model for predicting hourly, weekly or monthly electricity consumption. Gonzalez and Zamarreno (2005) forecasted short-term electricity load with a neural network which feed-back part of its output into the system (recurrent network). To further buttress the point, Azadeh et al., (2008) estimated the long-term annual electricity consumption in energy-intensive manufacturing industries with feed-forward neural network, and concluded that neural network is very applicable to the problem when energy consumption shows high fluctuation. Radial basis function (RBF) neural networks have also been used in modelling time-series data and the results found to be precise than its equivalent back propagation networks (Wu & Liu, 2012; Noor et al., 2011; Frimpong & Okyere, 2012; Olanrewaju, Adisa & Pule, 2012; and Bonanno et al., 2012), implying that it might provide even better forecasting for electricity consumption.

In this paper, an Electricity Consumption Prediction System (ECPS) whose predicted outputs are based on the principle of RBF neural network is carried out. The study also seeks to compare the performance of RBF network with backpropagation (BP) networks which have been the most familiar ANN models for time-series prediction over the last decade.

RELATED WORKS

Over the last few decades a number of prediction approaches and models have been developed. These approaches are mainly Statistical or Artificial Intelligence based. Statistical approaches usually involve 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 (Sarlak et al., 2012). Statistical and also Artificial Intelligence (AI) approaches, each one includes several techniques that are discussed below;

Ma et al., (2010) employed integrated multiple linear regression and self-regression techniques to forecast monthly electric energy consumption for large scale public buildings. In the work of Cho et al., (2004) the regression model was developed on 1-day, 1-week, 3-month measurements, leading to the forecast error 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 model. Mohamed and Bodeger (2005) proposed a multiple linear regression model using gross domestic product (GDP), price of electricity and population as chosen variables deemed most influencing for New Zealand electricity consumption. The result showed that the forecast is almost equivalent to the national forecast with 89% accuracy. Kimbara et al., (1995) developed an Auto-Regressive Integrated Moving Average (ARIMA) model to implement on-line forecast. The model was first derived on the historical loads, and was then used to forecast load profiles for the next day. Auto-Regressive Integrated Moving Average with external inputs (ARIMAX) model has also been applied to some applications, forecasting the electricity demand of the buildings (Hoffman, 1998). Arimah (1993) has forecasted electricity consumption in residential, commercial and industrial sectors in Nigeria using a Log-Linear Regression model and consumption data obtained from Central Bank of Nigeria (CBN) annual statistical bulletin for the period of 1964-1989. The result shows that electricity demand by different classes of consumers, with respect to independent variables, is inelastic and has implications on the future growth in demand for energy. In similar vein, Ghaderi et al., (2006) estimate electricity demand function for 17 groups of industries in Iran, using a Log-Linear Autoregression model with annual time-series data from 1980 to 2002. The estimated results from the model indicated the weak sensitivity of industrial energy consumption to price change which is the principal independent factors among the number of economic variables. As can be seen from the above cited works, statistical approaches require large quantity of information relevant to appliances, customers, and other economic variables, which may not be readily available. In other words, the outcomes of their predictions may be dependent on some unknown variables, whose effect on the process cannot be estimated and usually contain noise that cannot be cancelled out. According to Sarlak et al., (2012) statistical approaches do not produce satisfactory results when used to estimate electrical energy consumption because its effectual factors are strongly nonlinear and complicated.

AI techniques, such as ANN, Fuzzy Logic and Genetic Algorithms (GA) have been employed to improve the forecast accuracy and reliability of a chaotic system such as load forecast, energy consumption forecast, capital market stock performance prediction, students' academic performance estimation, population estimation etc. (Liang & Cheng, 2010; Otavio et al., 2004; Papadakis et al., 2003; Karabulut et al., 2008; Grando et al., 2011; Wu & Liu, 2012; Lykourentzou et al., 2009). In the area of electricity usage, early studies have successfully used neural networks to model the time-series of electricity consumption. Nizami and Al-Garni (1995) applied a simple feed-forward neural network to relate the electricity consumption to the number of occupancy and weather data. Gonzalez and Zamarreno (2005) estimated short-term electricity load with a special neural network which feeds back part of its output. Azadeh et al., (2008) forecasted the long-term annual electricity consumption in high energy-demanding manufacturing industries, and showed that the neural network is very applicable to this problem when energy consumption shows high variation. Sarlak et al., (2012) proposed backpropagation (BP) network for enhancing the accuracy of daily and hourly short-time load forecast of Iran using the country's power consumption data for the year 1994 through 2005. Most of the early study discussed above, proposed backpropagation neural networks, sometimes called multilayer perceptrons (MLP), however, other ANN model are beginning to attract attentions. Lendasse et al., (2008) applied Self-Organizing Maps (SOM) to the estimation of electricity consumption of Poland, and when compared with other linear and nonlinear models, the results showed that SOM produced the best model. Grando et al., (2011) developed a 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 for the period of ten years (1998 -2008). The MSE of the system was found to be (0.00001). The applications of radial basis function (RBF) networks in the area electricity have also been reported in the literatures (Zhangang, Yanbo & Chen, 2007; Ghods & Kalantar, 2010; Zeng & Qiao, 2011; Bonanno et al., 2012).

A neural network is an artificial representation of the human brain that tries to simulate its complex learning process. Traditionally, the word neural network is describes to a network of biological neurons in the nervous system that process and transmit information. An artificial neural network (ANN) is a substantial parallel distributed processor made up of simple processing. ANN has the potential to be intrinsically fault-tolerant or capable of robust computation. Its performance does not degrade significantly under unpleasant operating condition such as detachment of neurons and noisy or missing data (Bernander, 2006). Since the country Nigeria is statistically underdeveloped compared with some advanced countries of the world, using ANNs may tend to contribute very significantly to the reliability and accuracy of electricity consumption forecast in the country. Therefore, this study applied the principle of RBF neural network to develop a system which can forecast the electric energy usage with high level of accuracy and reliability.

METHODOLOGY

General Method for Forecasting Electricity Consumption

The methodology for electricity consumption forecast is divided into seven (7) clearly recognizable steps (fig.1), as follows (Mulholland, 2008):

1. **Define Objectives:** The objective of electricity consumption forecast is to

conduct a detailed analysis which can be used to enhance planning and management of the power industry for efficient service delivery.

2. **Develop Historical Baseline:** Historical baseline is developed to obtain electric energy consumption (demand) data by different classes of consumers. Sources of data for historical baseline include; Energy Commission of Nigeria (ECN), Nigeria Electricity Regulatory Commission (NERC), National Bureau of Statistics, National Planning Commission of Nigeria, Power Holding Company of Nigeria (PHCN) and Central Bank of Nigeria (CBN) annual bulletins. For the purpose of this study, dataset was obtained from the Central Bank of Nigeria (CBN) annual statistical bulletins.
3. **Choose Forecast Method or approach:** The range of options where one can choose is given in fig. 1. For the purpose this study radial basis function (RBF) neural network was used to develop a model for electricity consumption forecast.
4. **Determine and Review Assumptions or Parameters:** As earlier stated, future projection with statistical approaches are dependent on assumptions about populations and economic variables while the success of AI approaches depend on the parameters adjustments. For instance, in ANN, parameters such as number of neurons, training function, transfer function, and number of layer or nodes are very important to the projection results.
5. **Apply model or approach**
6. **Evaluate forecast output:** Forecast results should be evaluated to ensure that it meets the original objectives. Assumptions or parameters may be revisited to improve the accuracy of the forecast.
7. **Use the forecast outputs or results for policy and decision-making:** Prediction results of electricity consumption should serve as the platform and guide for policy formulation and decision-making by the concerned stakeholders.

Theoretical Framework

Having considered the general methodology for developing a forecast system in the previous section, it is pertinent to discuss the methodology that is specifically used to develop Electricity Consumption Prediction System (ECPS). Several software development process models are available each with inherent strengths and weaknesses. In this study, ***spiral model*** (fig.2) proposed by Barry Boehm in 1986 was adopted because it is an iterative model and allows developer to revisit a particular phase(s) and make adjustment. The Steps involved are as follows:

1. **Data collection:** The dataset used in this work was obtained from CBN annual statistical bulletin of 2006 (available at *www.cenbank.org/.../STAT BULENTIN/*...). This was the last CBN report that presented information relating to electricity consumption in Nigeria. The data show the electricity consumption (in Megawatts per hour-MWh) by three classes of consumers: Residential, Industrial and Commercial consumers with their respective percentages for the period of 1980-2005.
2. **Data Pre-processing:** In the pre-processing phase, the datasets that were used to train, validate and test the model were extracted. The consump-

tion data for the period of 1980 to 2005 containing 208 dataset was used to train, validate and test the proposed models in the ratio of 13:3:4 implying that 65% of the entire data for training, 15% for validation check and 20% for testing. Also, data for the period of 2006-2013 were extrapolated and used as part of test data.

3. **Data preparation:** The training dataset were used for the training and validation of the models constructed in the next phase. The input data were organized in a manner suitable for coding within the premise of ANN (matrix form). As part of the preparation, the entire dataset was divided into two: the input variables and the output variable.

i. **Input variables:** There are seven (4) input variables namely; consumption year*, **Residential consumption, Commercial consumption, Industrial consumption with their respective percentage*** and ***Total consumption*** (Target values) which serve as input to the constructed model.

ii. **Output variable:** There is only one output variable; the ***Predicted Output*** simulated by the ANN models created.

4. **Model construction:** The dataset prepared in the previous phase was used to create, train, validate and simulate the neural network which serves as the backbone to ECPS. Our principal focus is the RBF network, but since we also intend to compare the accuracy and reliability of RBF network with the back propagation (BP) neural networks, we also used the same dataset to simulate two different types of BP networks namely; Feed-forward BP network (BP1) and Elman BP network (BP2). All the neural network models were created using the ***nntool*** command of MATLAB toolboxes.

5. **Model testing, validation and results simulation:** After the models have been created, they were trained, tested and validated on the new datasets that were not used during the training session, and the results simulated. These results are the predicted outputs generated by the RBF network and BP networks. Section 4 presents the algorithms for training the ANN models created in this phase.

6. **ECPS coding:** In this phase, the relationship between predicted output of RBF network and the target values (Total consumption) was computed and the results were used for coding Electricity Consumption Prediction System (ECPS). The source codes for ECPS were written in Visual Basic. Visual Basic is an event-driven tool that allows the developer to develop Windows (Graphic Users Interface-GUI) application and has the ability to handle fixed and dynamic variable. The characteristics of ECPS include graphical user-interface; extremely large knowledge bank; ability to forecast up to 1000 years; and fast execution time.

7. **ECPS Testing and Integration:** After coding, the system was subjected to series of usability tests and integrated into a stand-alone system with SQL Server 2008. Fig.3 depicts the logical interaction between the user and ECPS. As can be seen from fig.5, the user of electricity forecast reports makes prediction request via the ECPS interface by supplying the necessary data such as base year and limit (1-1000), the interface send the request direct to the knowledge base for pattern matching while RBF network designed with MATLAB performs the necessary computation and the results returned to the user via the same interface. The func-

tion of the Administrator is to provide the necessary backend assistance that might be required by the system/users.

8. **Evaluation:** In this phase, the accuracy of ECPS results was analyzed and compared with the results predicted by equivalent BP networks and the results presented in section 5. Measures such as training time, mean square error (MSE), sum of square error (SSE) and correlation coefficient (R) were used for performance evaluation.

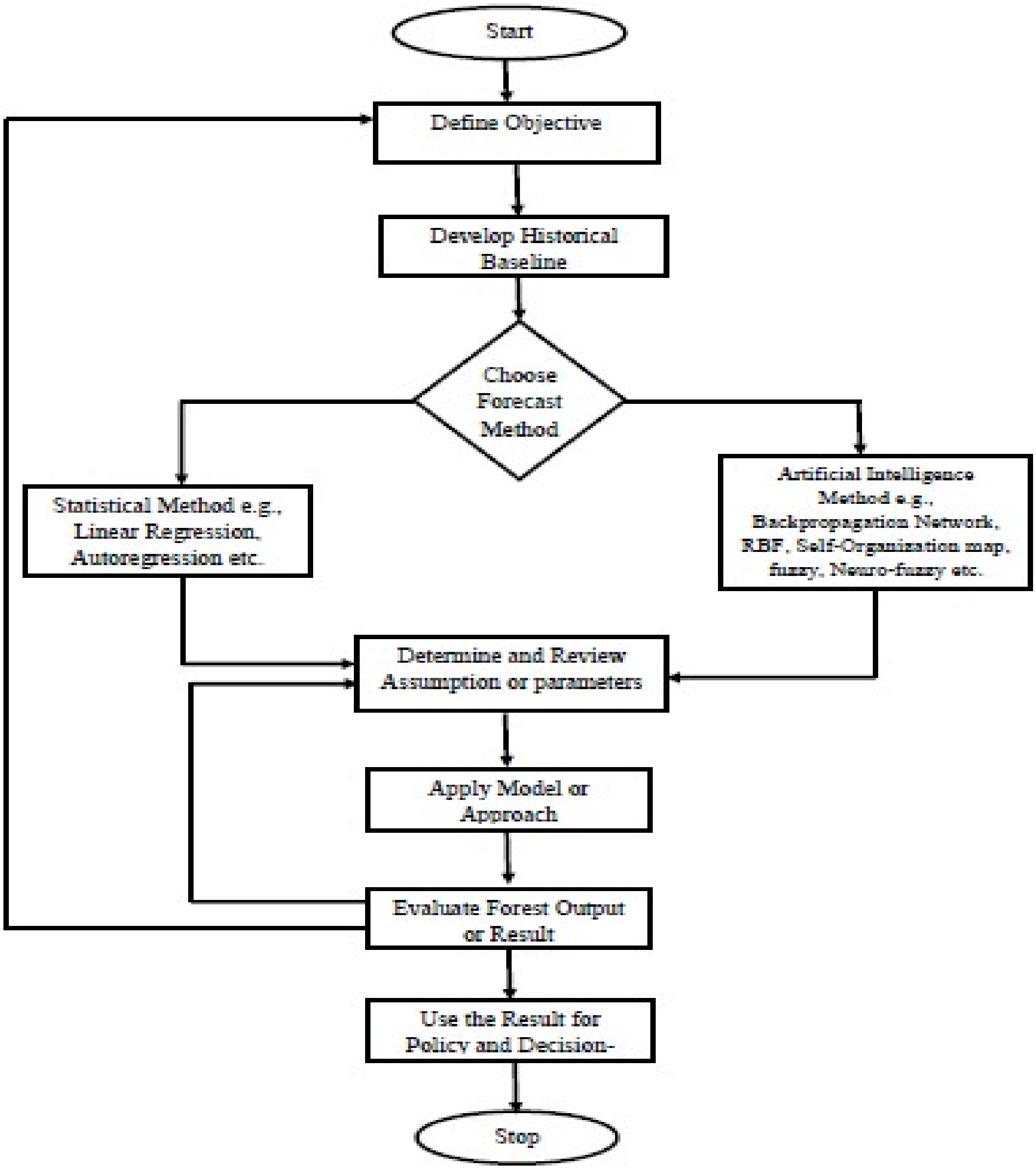

Fig. 1: General Method for Forecasting Electricity

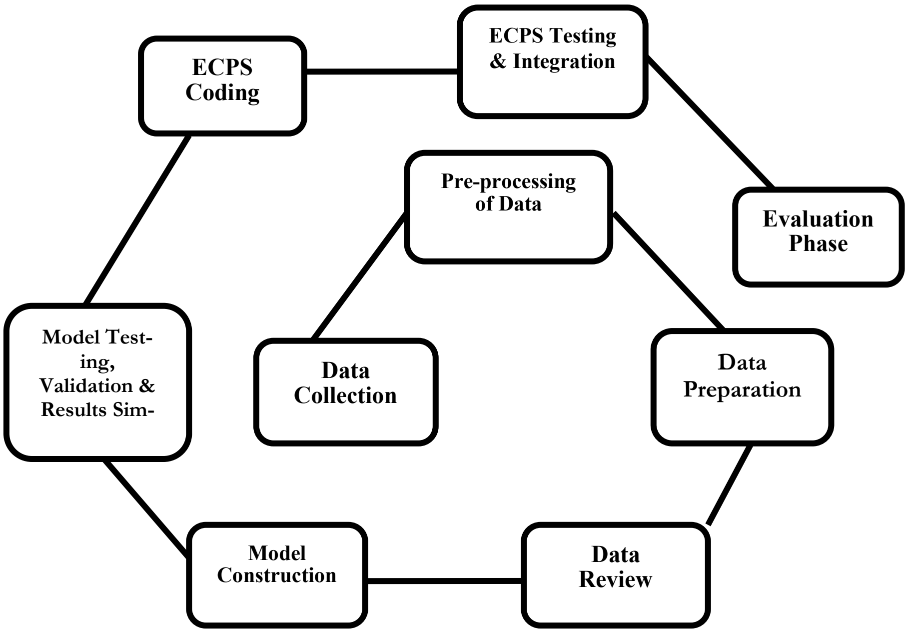

Fig.2: Spiral Representation of the Methodology for Developing ECPS

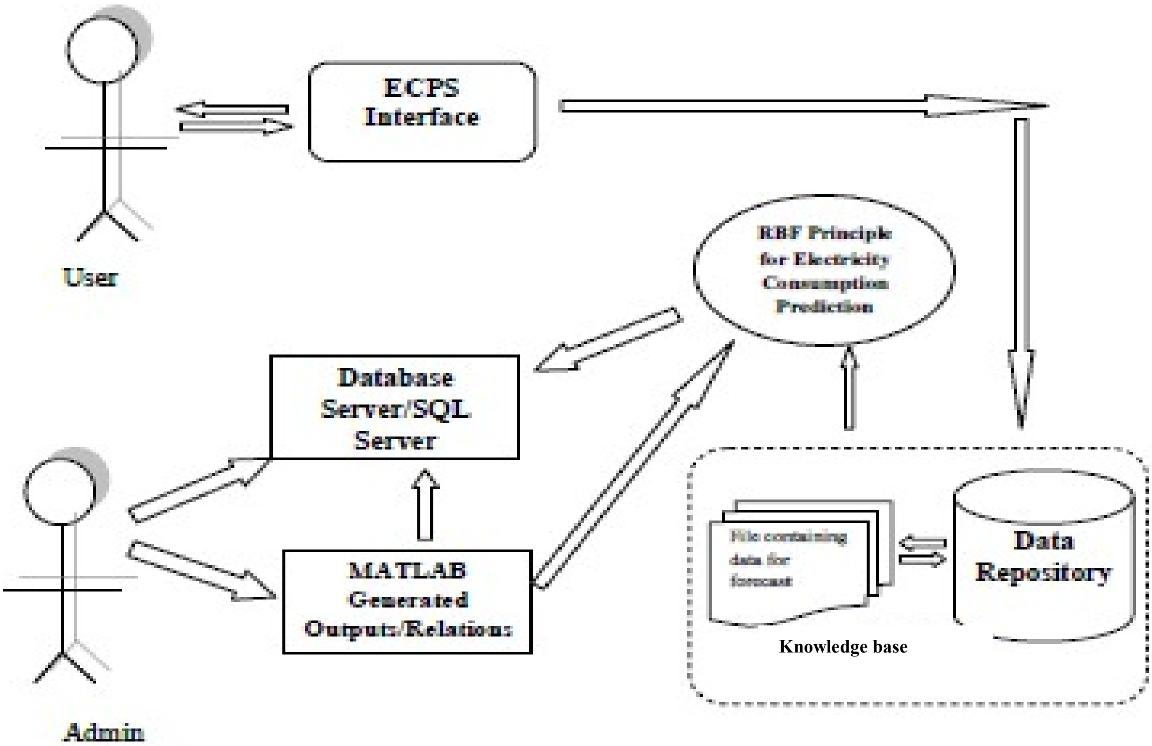

Fig.3: Logical Interactions between the User and ECPS

Principle of Radial Basis Function (RBF) Network and Training Algorithm

Radial basis functions (RBF) neural network is one of the vital tools in solving problems involving time-series regression and in pattern classification pioneered by Broomhead and Lowe (Broomhead & Lowe, 1988). A RBF neural network uses radial basis functions as an activation functions and comprises a linear combination of radial basis functions pattern recognition and control. RBF neural network can estimate any continuous function mapping with a reasonable level of precision. Fig.4 depicts architecture of a RBF neural network. The network consists of three different layers: input; hidden and output layer. The bell-shaped curves in the hidden nodes indicate that each hidden layer neuron represents a radial basis function that is centred on a vector in the feature space. From the first layer, the input signals (x_i) composing an input vector is sent to a hidden layer (second layer) composed of RBF neural units. The third layer is the output layer, and the transfer functions of the nodes are linear units. Connections between the input and hidden layers have unit weights. The hidden layer of the RBF network has many forms of radial basis activation function (Wu & Liu, 2012). While the hidden layer performs a nonlinear transformation of input space, resulting in hidden space of typically higher dimensionality than the input space, the output layer performs linear regression to forecast the desire target values (Haykin, 1999). The input vector is fed to each *jth* hidden node where it is put through that nodes radial basis activation function defined in equation (1):

$$\alpha_j = f(x_i) = exp\left[\frac{-\|x - c_j\|^2}{2\sigma_j^2}\right] \qquad (1)$$

where $\|x - cj\|$ is the Euclidean norm distance between the feature vector x and the center vector c_j for that radial basis function.

The values α_j are the outputs from the radial basis functions. These radial basis functions are on a 2-dimensional feature space (Fig.5).

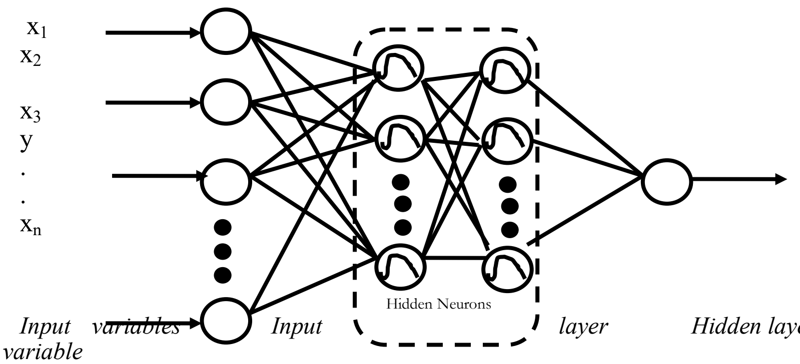

Fig.4: RBF Neural Network Architecture

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

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

As can be deduced from fig.5, the value (α_j) equidistant from the center in all directions have the same values. So this is why they are called *radial basis function*. The network output y is formed by a linearly weighted sum of the number of basis functions in the hidden layer. The values for the output neurons can be defined as:

$$y_k = \sum_{j=1}^{n} w_{jk}\alpha_j \qquad (3)$$

where y_k, the *kth* component of the y, is the output of the *kth* neuron in the output layer, w_{jk} is the weight from *jth* hidden layer neuron to the *kth* output layer neuron, and αj is the output of the *jth* node in the hidden layer. With the described architecture, 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 (Wu & Liu, 2012).

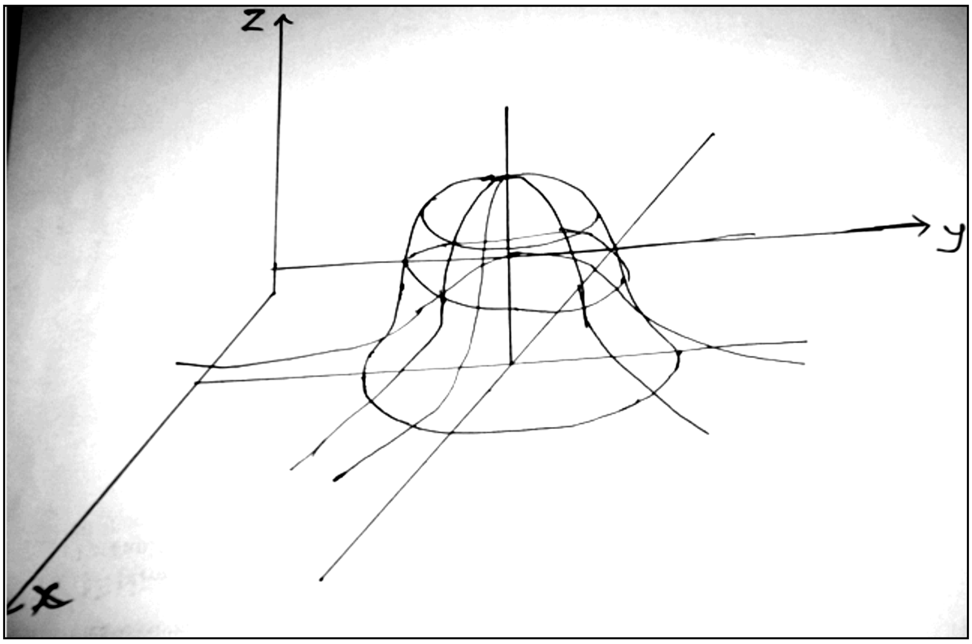

Fig.5: 2-Dimensional Feature Space of RBF

Training of ANN models is tailored towards minimizing the sum of square errors (SSE) defined in equation *(4) as*:

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

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 and k is number of cases. In this study, we do not present the training algorithms for BP networks that were compared with RBF network we are focusing. The training algorithm for the two BP networks used is this research is *Gradient Descent Backpropagation* algorithm (Levenberg-Marquardt) similar to that used by Haykin (1999); Lykorentzou et al., (2009); and Folorunso et al., (2010). For RBF network, the SSE can be minimized by adjusting the parameter w_{jk} in *eqn (3)* in a manner similar to Backpropagation (BP) network. There is only one set of parameters instead of two as the case with BP networks. Upon suppressing the index *q (q=i)*, we have our SSE, simply represented as *E*, to be:

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

$$E = \frac{1}{k}\sum_{i=1}^{k}\left(t - \frac{1}{j}\sum w_{jk}\alpha_j\right)^2 \qquad (6)$$

Differentiating *E* with respect to w_{jk} yield;

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

Substituting this into the steepest descent method;

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

where η is the learning rate. Upon training over all Q feature vector, *eqn (8)* becomes;

$$w = w + \left[\frac{2\eta}{JK}\sum_{q=1}^{Q}\sum_{i=1}^{J}(t_k - y_k)\right]\cdot\alpha_J^Q \qquad (9)$$

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) and 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, M and the spread parameter σ remain unknown. There are different methods to get this 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* $m=1, \ldots, Q$. 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. Another method is to use the exemplar vector as the first Q centers, and then to generate many more centers at random in the feature space. Thereafter, the distance between centers is computed and any center that is too close to another center is eliminated. However, we should have significantly more centers than there are classes. The threshold for elimination can be, say, 0.4 times the average distance between centers. Then σ can be taken to be from 0.25 to 0.50 times the average distance of the remaining centers (the radial basis functions will overlap some, but not too much). To implement *equation (9),* follow these steps:

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 average distance between centers, eliminate 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: Computer and y_k, and then *E*.

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

Backpropagation Networks and Algorithm

Backpropagation networks, sometimes called multilayer perceptrons have been applied successfully to solve complex and diverse problems by training the network in a supervised manner with a highly popular algorithm known as the error backpropagation algorithm. The algorithm, according to Caudill and Butler (1992), is based on the determining the error between the predicted output variables and the target values of the training dataset. The error parameter is commonly defined as the root mean square of the errors for all the data points used in the training. The weight factors are adjusted by determining the effect of changing each weight on the error in the predicted outputs. This process takes the form of determining the partial derivatives of the errors with respect to each of the weights. The algorithm used to propagate the error correction back into the network according to them is generally of the form:

$$w_{ij}^{new} - w_{ij}^{old} = -\eta \frac{\partial E}{\partial w_{jk}} \qquad (10)$$

EXPERIMENTAL RESULTS AND INTERPRETATION

Both the training and projection were performed on an HP PC with 1.66GHz Genuine Intel (R) Dual Core(s) processor, 2.00GB RAM and 150GB Hard disk on Microsoft Window 7 Home Basic Edition Operating System. Neural Network Tool *(nntool)* of MATLAB was used to create, train, validate and simulate results from the neural network models used in this study whereas Visual Basic used to code the ECPS interface. As established in the previous section, the data used for the experiment comprises the nation's electricity consumption with time series of 25 years (1980-2005) and data size 208. The data for the period of 2006-2013 were extrapolated and used during the testing phase. The two backpropgation networks (BP1 and BP2) that were compared with RBF network model, were selected based on their simplicity and perceived-ease of use, and maintained the same Sigmoid activation function in the computation of their outputs. All the three networks have the same topology of (7-10-1) implying that, each has 7 nodes at the input layer, 10 nodes of two layers in the hidden layer and only 1 node at the output layer (as shown in fig.4). Also worth of note it that, 65% of the datasets was used for the training, 15% for validation while the remaining 20% was used for testing. Table 1 shows the results simulated by the three network models and their respective square errors. During the experiments for each network model, the training is set to terminate at 1000 iterations. Measures for evaluating the performance of the three networks are shown in Table 2. These include training time (Time), sum of square error (SSE), mean square error (MSE) and correlation coefficient (R) between target output and the predicted outputs by the networks, where $-1 \leq R \leq 1$. When prediction is perfect, then R=1. The purpose of finding R is to determine if there exist any positive relationship between the target values and the output simulated by the models.

Table 1: Experimental Results

Year	Target Values (MWh)	Simulated Results BP1 (MWh)	Square Error (BP1)	Simulated Results BP2 (MWh)	Square Error (BP2)	Simulated Results RBF (MWh)	Square Error (RBF)
1980	752	962.0837	0.0780457	752.7408	0.0000010	750.0014	0.0000071
1981	847	965.3129	0.0195118	772.4513	0.0077466	846.0001	0.0000014
1982	955	952.4229	0.0000073	852.0641	0.0116179	955.1187	0.0000000
1983	955	945.9133	0.0000905	792.6400	0.0289036	955.0001	0.0000000
1984	793	941.8295	0.0352234	752.5889	0.0025969	790.0003	0.0000143
1985	923	996.9764	0.0064237	702.5054	0.0570680	923.0100	0.0000000
1986	1147	1355.6767	0.1269501	937.5810	0.0333354	1147.0010	0.0000000
1987	1366	1612.4066	0.0325389	1064.7711	0.0486286	1366.0000	0.0000000
1988	1754	1991.5114	0.0183362	995.4188	0.1870445	1759.2210	0.0000089
1989	2045	2000.3100	0.0027025	1007.4872	0.2573951	2045.0000	0.0000000
1990	2332	2327.8683	0.0000031	1701.4635	0.0731077	2322.7891	0.0000156
1991	2707	2707.9539	0.0000001	2267.9937	0.0263006	2707.0531	0.0000000
1992	3317	3787.0008	0.0201403	3330.3238	0.0000161	3317.0000	0.0000000
1993	3617	3910.5501	0.0065867	2845.7681	0.0454646	3616.9990	0.0000000
1994	4178	4179.5856	0.0000001	2752.0001	0.1164936	4178.2000	0.0000000
1995	5066	4967.3151	0.0003795	2752.3332	0.2085793	5066.1120	0.0000000
1996	6899	6418.2186	0.0048565	3052.2589	0.3108949	6898.0000	0.0000000
1997	5621	5276.7021	0.0006590	2992.4311	0.2186813	5621.0006	0.0000000
1998	5970	5694.4270	0.0021307	3752.9211	0.1379157	5970.1000	0.0000000
1999	6000	5625.8150	0.0038893	1892.2894	0.4687024	6020.0010	0.0000111
2000	5568	5364.2049	0.0013396	2752.9105	0.2556148	5569.0011	0.0000000
2001	6285	7312.3110	0.0267173	1909.7881	0.4846047	6284.6700	0.0000000
2002	7375	7076.5203	0.0016380	2655.2200	0.4095618	7374.2207	0.0000000
2003	7471	7191.4598	0.0013308	3712.0184	0.2531529	7471.4167	0.0000000
2004	7475	7448.0097	0.0000130	2001.5296	0.5361708	7474.9900	0.0000000
2005	8019	7608.1093	0.0026255	1702.3331	0.6204911	8019.0011	0.0000000

Table 2: Measures for Performance Evaluation

Network Models	Time (s)	SSE	MSE	R
Feed-forward Backpropagation (BP1)	12.0	0.3921396	0.01508229	0.993060432
Elman Backpropagation (BP2)	0.05	4.8000898	0.18461884	0.733494599
Radial Basis Function (RBF)	0.09	0.00005843	0.00000225	0.999998491

In Table 1 above, outputs simulated by the three networks are given in 4d.p while their square errors are given in 7d.p. In each case, the square error is calculated with the formula;

$$Square\ Error = \left[\frac{Target\ Output - Network\ Output}{Target\ Output}\right]^2 \qquad (11)$$

Also, SSE, MSE and R values in Table 2 are displayed in 8d.p while the training times are given in 3s.f. As illustrated in Table 1 and Table 2, BP1 returned the least square error in the year 1991 and 1994 with value 0.0000001 each while the maximum square error was generated in the year 1996 with 0.1269501. This implies that BP1 showed the best performances in 1991 and 1994; and worst performance was observed in 1986 respectively. The training time of BP1 is 12.0 seconds; the SSE value is 0.3921396 while the MSE value is 0.01508229. The graph in fig.6 (a) showed that BP1 is effective at minimizing the mean square errors generated during the training session. There is high positive correlation between the target values and the values simulated by this neural network model (R=0.993060432) meaning that the model predict the target outputs with reasonable level of precision. With BP2, square error generated is least in 1980 with 0.0000010 and maximum in 2005 with 0.6204911 indicating that the best performance was shown in 1980 and the worst in 2005. Out of the three neural network model compared, the highest SSE and MSE values were observed in BP2 with 4.8000898 and 0.18461884 respectively. This implies that this network is poor at minimizing the performance criterion. The correlation coefficient (R) between the output simulated by this network and target values is 0.733494599. The graph of fig.6 (b) showed that the performance of the model is poor at minimizing the mean square errors with the training time of 0.25 seconds. Finally, RBF neural network returned the least possible square errors as it predicts the exact values as target, in many cases and less significant errors in some other cases. For instance, the network returned square errors of 0.0000071 in 1980, 0.0000014 in 1981, 0.0000089 in 1988 and finally 0.0000111 in 1999 respectively. As observed from Table 1, there were slight differences between the target values and the results simulated by the models for other consumption years. The value simulated for other years were the same as the target output. Performance plot of fig.6 (c) also confirmed that RBF model is very effective and efficient at minimizing the criterion objectives with SSE and MSE values of 0.00005843 and 0.00000225 respectively.

This implies that, RBF network is able to map the input vectors with the output vector with high level of accuracy. Correlation coefficient (R) value of 0.9999998491 was observed between the target values and the simulated results. This clearly indicates that the RBF network has shown the best performance in modelling the time-series prediction of electricity consumption which is a chaotic system. This is because RBF network, being a local approximator, and has the ability to minimize the noise that can hinder the accuracy of the predicted values in the course of its function approximation. Results from Table 2 also confirmed earlier research that the training of RBF network is faster than the Backpropagation networks (Wu & Liu, 2012), with Time=0.09 seconds. This is made possible as it performs both linear and non-linear approximation at different layers of its network model.

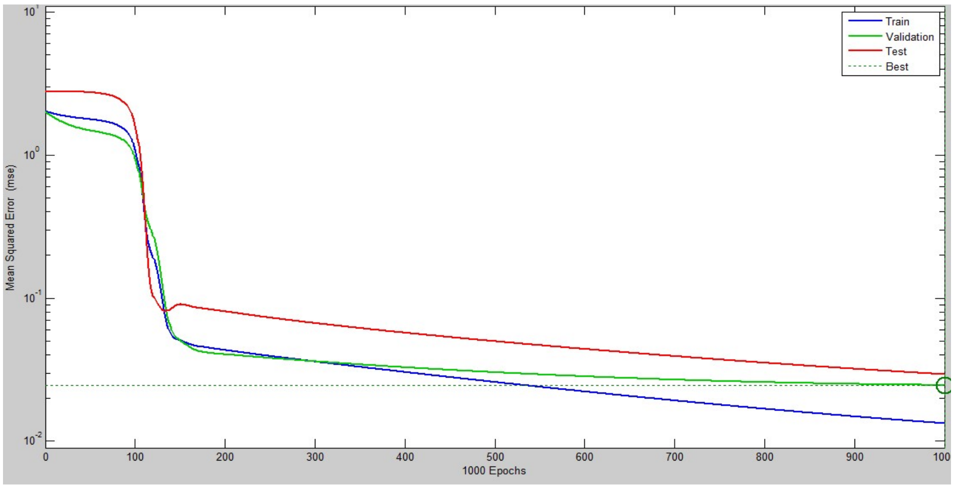

Fig.6(a): BP1 Network

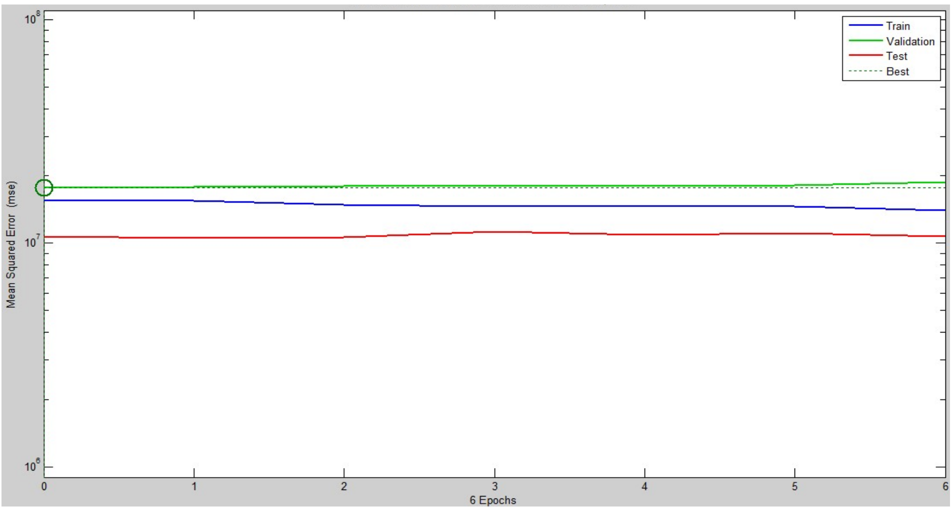

Fig.6(b:) BP2 Network

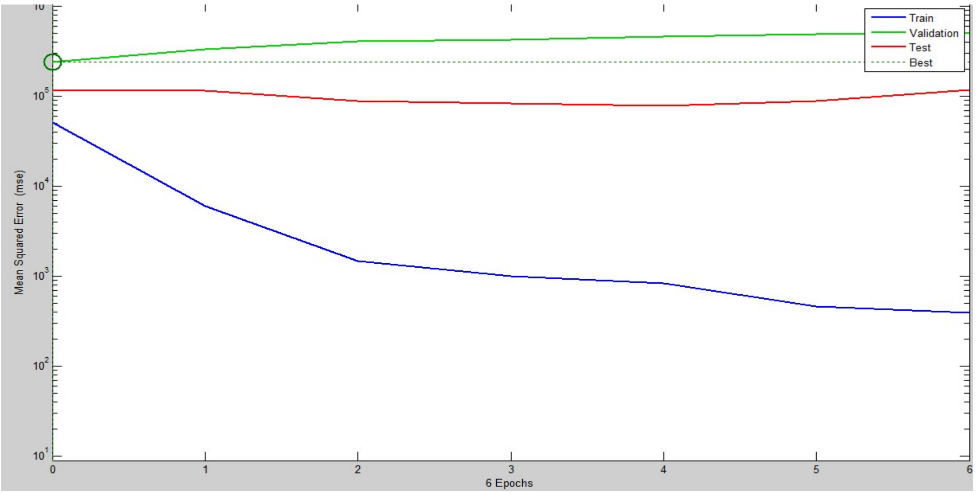

Fig.6(a): RBF Network

Figure 6: Neural Network Training

Fig.7 shows the graphical comparison of the target output and the values produced by the three networks. As can be seen from the graph, the output of RBF network is comparable with the Target output. The output of BP1 is also good to some extent while BP2 shows poor performance. BP1 and BP2 serve as check on the consistency of RBF network.

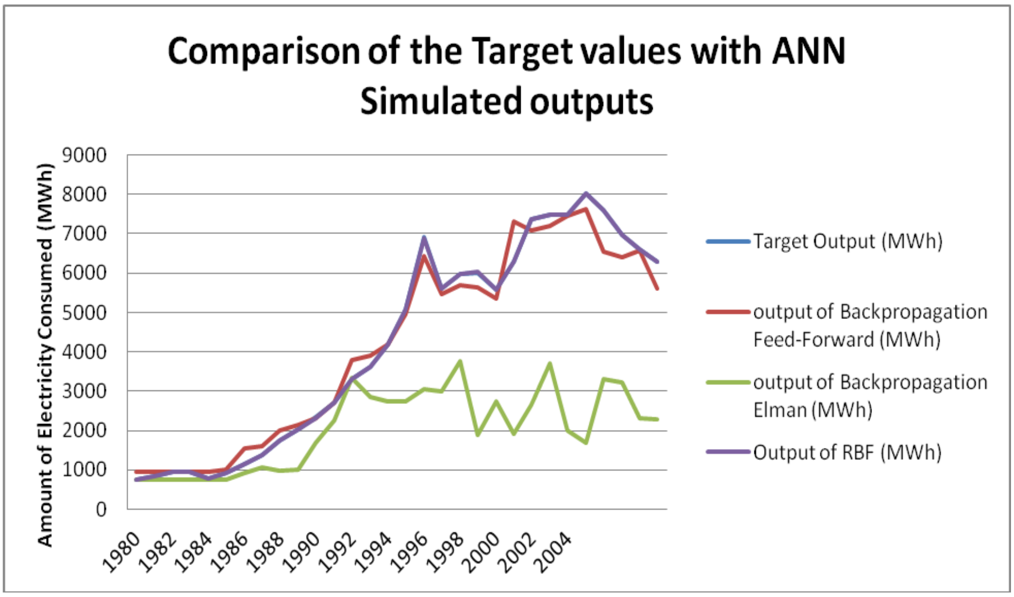

Figure 7: Comparison of Target Outputs with Simulated Outputs

ELECTRICITY CONSUMPTION FORECAST WITH ECPS (BEYOND 2006)

The actual forecast of electricity consumption into distance future was done using ECPS and the results shown in fig. 8. This results display the target outputs, predicted output and percentage accuracy of the prediction. With ECPS, it is possible to supply the number of forecast years and view the results. Example of such forecast for year 2022 is shown taking 2012 as the base year is shown in the figure. The extrapolation of the historical data is done to compute the target output while RBF network simulated the predicted results. The percentage accuracy of RBF network's forecast is shown at the fourth column of the figure.

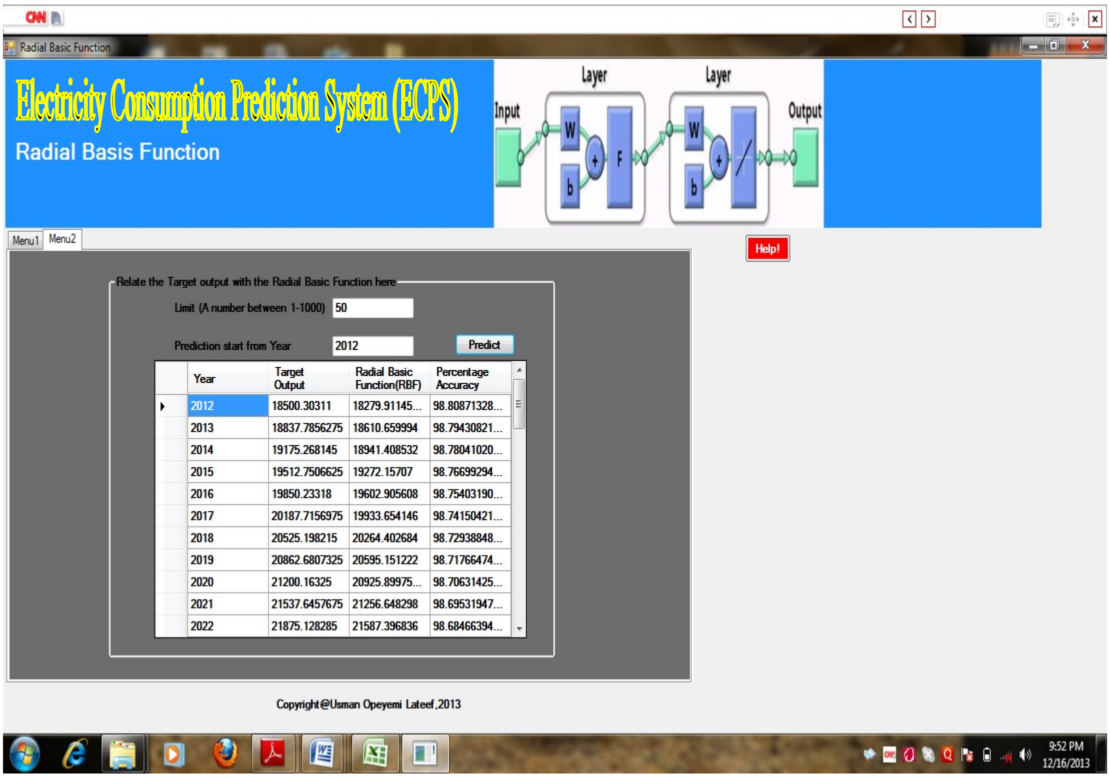

Figure 8: Prediction Interface

CONCLUSION AND FUTURE WORKS

The results obtained from the study actually showed that Radial Basis Function (RBF) networks are capable to forecast the electricity consumption with a high level of accuracy and precision than its equivalent Backpropagation (BP) networks. This we are able to prove from the computation of sum of square error (SSE), mean square error (MSE) and the correlation coefficients (R) of network models used. Although, the performance of feed-forward BP network (BP1) is quite impressible in the projection of nonlinear phenomena, but not as efficient and reliable as a RBF neural network. Our experiments confirmed that a RBF network has demonstrated a very powerful function approximation and estimation properties, and the principle can be used to design; code and implement an efficient and reliable prediction system. The accrued benefit of such system will result into efficient service delivery by the stakeholder in the power supply sector of the economy. Further research can be tailored towards comparing the predicted results of electricity consumption using the proposed model with equivalent artificial intelligence approaches such as self-organizing map, liquid state machine, support vector machine, case-base reasoning, neuro-fuzzy predictor etc., and using statistical tools to verify if there exists a significant difference between the outcomes.

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