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Development of an Artificial Neural Network Model For Daily Electrical Energy Management

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ABSTRACT

Efficient monitoring and control of electrical energy do not only prevent fire out-breaks caused by electrical appliances, but can also reduce excessive billings and prevent electrical installations. Most Energy Management Systems (EMS) for remote controlling of electrical appliances rely mostly on sensors, data and GSM networks which are un-reliable or even un-available in most part of developing world, this makes them less reliable. Therefore, there is need for an intelligent system that can manage electrical consumption intelligently using user-appliance interactive pattern over time. This paper proposes an Artificial Neural Network (ANN) model that learns user-appliance interaction over a period of time for intelligent control of users' appliances in his/her absence. The model parameters (number of neurones and training algorithms) that affects its performance were first investigated and adopted. The performance of the developed model was evaluated using Regression analysis (R) and Mean Square Error (MSE) using ANN and Simulink tool boxes in Matlab R2015b. A good model performance was achieved with R = 0.92309 and MSE = 0.038589. The results imply that the developed model can be used for real time control when deployed. Also, Scale Conjugate Gradient (SCG) training algorithm should also be used because of its high performance for pattern recognition problems. This work will go a long way in efficiently controlling household electrical appliances in the absence of the users thereby preventing fire disasters caused by electrical appliances, reducing the tariffs of consumers while increasing the lifespan of electrical installations.

Keywords: *Artificial Neural Network, Electrical energy, Energy Management Systems, Pattern Recognition.*

1 INTRODUCTION

Electric energy is one of the essential need of people all over the world because of its importance in the development and economic growth of any nation (Titus *et al.,* 2013). Energy management schemes to monitor, control and conserve energy in a smart home context is one of the best approach to address energy wastages especially in developing countries where about 60% of the population are without electricity (Mohammed and Khan, 2009; IEA, 2003). Statistics show that approximately 40% of the overall world-wide energy consumption are due to energy consumed in residential and business buildings (EIA, 2014).

The major causes of this influx in energy consumption in buildings are due to the activities of space heating and conditioning, water heating, lighting, and the use of computers and other electronic devices (IEA, 2003). According to IEA, 30% electrical energy can be saved with proper energy management. In view of this, smart homes systems have been developed to manage energy consumption in residential buildings and offices. However, most of the developed systems are Wireless Sensor Networks (WSN), GSM networks and computer vision based dependent technologies deployed in the context of Internet of Things. These techniques heavily rely on constant availability of GSM network coverage and internet data services which are very un-reliable in most developing countries, hence, making them unreliable and in-efficient.

There is therefore need for an intelligent pattern recognition system that can learn and autonomously control electrical appliances using users' interactive pattern with the appliances. This will assist in reducing over billing, fire out-breaks which are caused by electrical appliances and completely solve the problem of relying on data or GSM networks. The aim of this work is to developed an intelligent Artificial Neural Network (ANN) based pattern recognition model that learn users interactive pattern with some selected electrical appliances and deployed for controlling energy usage and monitor consumption. Two ANN parameters (Number of Hidden Neuron and training Algorithms) were investigated to determine their effect on the performance of the model. This is because the parameters affect the generalization capability and convergence of any ANN (Basheer & Hajmeer, 2000). The model was designed, developed and simulated in Matrix Laboratory (MatLab) Version R2015a programming environment. In addition, the performance of the system was evaluated using Regression (R) and Mean Squared Error (MSE) and the model was deployed using Simulink.

Hwan et al., (2015), proposed an ANFIS-based energy management inference algorithm with scheduling technique for legacy devices. Sensor data and power usage pattern of equipment are used as input variables and a device control signal is the system output. Data bank receives inputs at each step and stores them in order that the decision block trains the ANFIS. When the retraining signal is entered into the ANFIS, new parameters of the ANFIS are updated. The disadvantages with this conventional EMS is that these power saving devices was newly installed instead of well-functioning existing home appliances in spite of their remaining durability.

Teich *et al.,* (2014), designed a neural network for smart homes and energy efficiency. This project has unique factor combinations of building specifics, user profiles and external influences lead to the necessity of self-adaptive systems for personal comfort. This work is limited to room temperature control. Teich et al (2014), a prototype neural network for smart homes and energy efficiency was developed. The system supports room temperature control in order to heat room's energy efficiently at a set time. This method is limited to energy consumption of a sensor nodes network itself and does not perform certain functions on behalf of user. Paradiso *et al.,* (2013), proposed a system on ANN-based appliance recognition from low-frequency energy monitoring data. This technique for recognizing appliance loads by exploiting low-frequency measurement data. The appliances are considered and not user-context.

De Paola *et al.,* (2012), proposed a system on an intelligent system for energy efficiency in a complex of buildings, automated Building Management System (BMS) technique was adopted. The system was able to monitor energy consumption, to sense environment conditions, and to modify these conditions through the actuators deployed into the environment, such as the HVAC (Heating, Ventilation and Air Conditioning) and lighting devices, in order to get the ambient conditions to the desired state. The system fails if the sensor readings are not accurate or faulty. Mahmoud *et al.,* (2012), worked on technologies in built environment to enable sustainable and energy conservation. The work was based on the use of real-time energy monitors (RTM) to influence behavior change in residential consumers and allow users to easily locate equipment/loads that are in standby/inefficient and causing energy waste in the real/physical environment. It cannot act on-behalf of the user because it only deals with monitoring. Biun *et al.,* (2012), worked on the design and implementation of a smart home energy management system with hybrid sensor network in smart grid environments. It was designed to make consumer devices more energy efficient and intelligent.

2 METHODOLOGY

The ANN model was trained and tested using the data collected from users' profile log. The data is described further thus:

2.1 DATA DESCRIPTION

The data used for the training and testing of the ANN model was collected using a users' profile log of users' daily interaction with the appliances under consideration. In the user profile data log as shown in Table 1, 24-hours information of users' were collected, that is "daily profile" about users' interaction with the appliances that most consume power and causes fire outbreaks (bulbs, fridge and heater) for five (5) days. The input data consists of the days (5) and time (every 20 minutes) while the output data consists of the status of the appliances at that particular time. "1" is recorded as an output when the appliance is "ON" and "0" when it is "OFF". A total of 324 data samples were collected.

TABLE 1: SAMPLE OF USER PROFILE DATA LOG

Input		**Output**		
Day	Time(Minutes)	bulbs	Fridge	Heater
1	12.00	0	1	0
1	12.20	0	1	0
1	12.40	0	1	0
1	1.00	0	1	0
1	1.20	0	1	0
1	1.40	0	1	0
1	2.00	0	1	0
1	2.20	0	1	0
1	2.40	0	1	0
1	3.00	0	1	0
1	3.20	0	1	0
1	3.40	0	1	0
1	4.00	0	1	0

The model block diagram is shown in Figure 1. The details of each block in the diagram is presented in subsequent subsections.

2.2 DATA TRANSFORMATION

The data collected was divided into training and testing dataset in the ratio of 8:2 respectively. The training set was used to estimate patterns between the input data and the output data, which allows the network to develop a relationship between inputs and the outputs was further divided into training, testing and validation in the ratio 6.5:2.5:1. The validation set is used to check how generalized the trained set can be while the testing set is used to test how efficient and accurate the neural network can predict the pattern of users' daily routine profile.

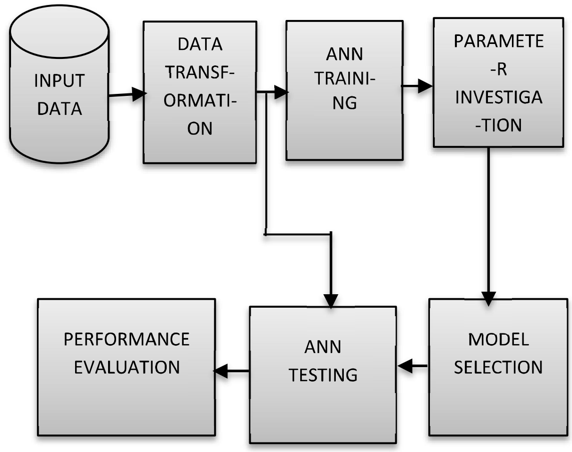


Figure 1: Model block diagram

2.3 ANN PARAMETER INVESTIGATION

Two important parameters that directly affects ANN generalization capability was investigated. The parameters are the number of hidden neurons and the training algorithms. Five different numbers of hidden neurons (1, 2, 5, 10 and 15) were investigated and their selection was arbitrarily while three training algorithms; Bayesian Regularization (BR), Levenberg Marquardt (LM) and Scale Conjugate Gradient training algorithms (SCG) were investigated In each case, the network was trained several times and the best performance was recorded for the three training algorithms the number of neurones adjusted in each case.

2.4 ANN TRAINING/TESTING

In order to develop a good ANN model, it must be designed. In designing the model, the parameters listed above were used. The designed model is shown in Figure 2. The network shows the input, hidden neurones and output neurones respectively.

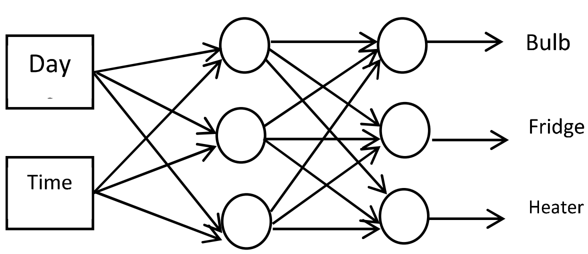


Figure 2: Designed ANN model

The designed model was trained and tested (investigation testing) for each number of neurone and each training algorithm. in each case, the model was saved after several training. The saved network was used for testing to determine the best model parameter under investigation for adoption. The best model adopted above was used to test (adopted model testing) the 20% data that was not used for training. Testing the model helps to determine how efficient and accurate the model has learned and how generalized it can be when deployed.

2.5 PERFORMANCE EVALUATION

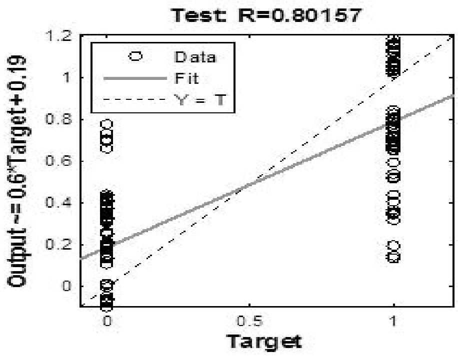
Performance Evaluation was carried out on the model to determine the best network parameters that will be adopted for the design and to check the overall performance of the adopted model. This research work based its evaluation on two key parameters; mean square error (MSE) and regression (R). Mean Square Error is the average of the square of the difference between each output processing element and the desired output while Regression is used to measure how fit the predicted output is to the desired output. A value of R=1 indicates perfect fit while MSE of zero (0) indicates no error.

3 RESULTS AND DISCUSSION

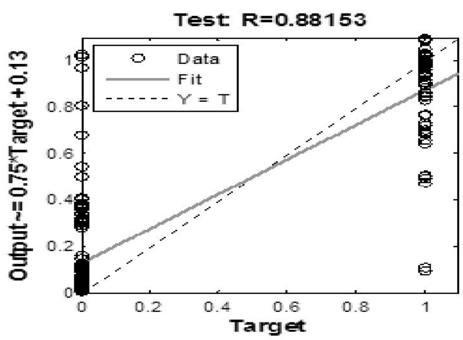
This chapter presents the results obtained from the various stages of the model development as shown in the overall work flow diagram in Figure 1 The model was trained and tested as described in Section 3.

3.1 ANN PARAMETER INVESTIGATION RESULTS

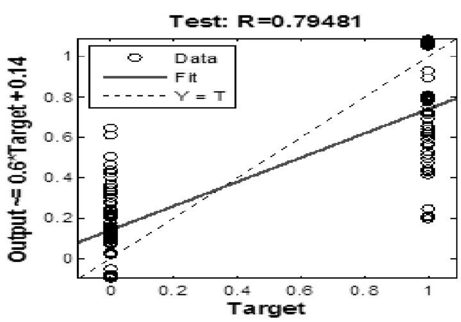
The ANN parameters investigated are; the Number of Hidden Nodes or neurones, and the training algorithm because of their effect in the performance of ANN generalization capability. Figure 4 shows the performance (evaluation testing, that is testing during training) of the three models trained with three different training algorithms for five (5) different hidden nodes (1, 2, 5, 10 and 15). Figure 3(a) and 3(b) shows the regression plots () for models trained with Bayesian Regularization Algorithm using one and two hidden nodes respectively. The results show that the model trained with 1 node have regression of 0.80157 while for 2 hidden nodes, regression value is 0.8815. Similarly, Figure 3(c), (d), (e) and (f) are regression plots for Scale Conjugate Gradient algorithm and Levenberg Marquardt for 1 and 2 neurones respectively. Other results are summarized in Table 2.



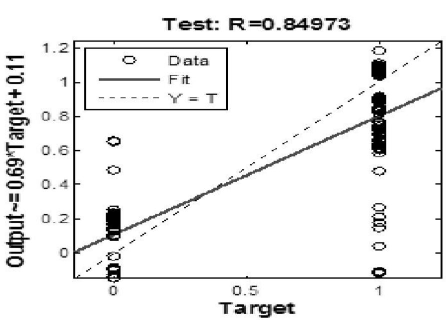
(a)



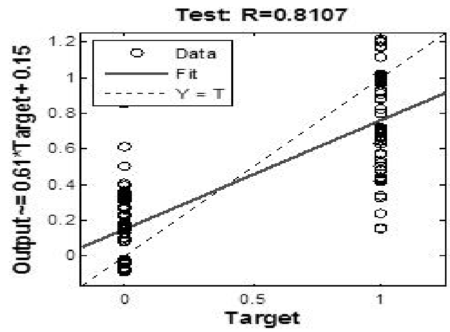
(b)



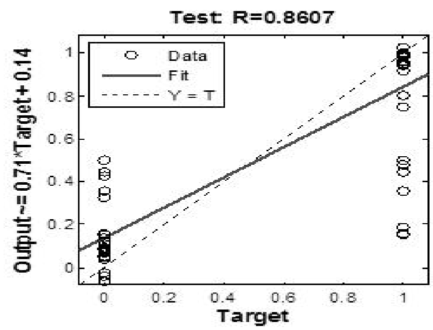
(c)



(d)



(e)



(f)

Figure 3: Regression plots for three training algorithms

TABLE 2: SUMMARY OF PERFORMANCE EVALUATION RESULTS

Hidden Node	**Levenberg Marquardt**		**Scale Conjugate Gradient (SCG)**		**Bayesian Regularization**	
	MSE	**R**	**MSE**	**R**	**MSE**	**R**
1	8.00426e-2	8.10700e-1	8.90638e-2	7.94813e-1	8.79749e-2	8.01566e-1
2	6.11450e-2	8.60696e-1	7.17314e-2	8.49733e-1	5.17375e-2	8.81531e-1
5	5.20230e-2	8.87241e-1	4.17674e-2	9.12346e-1	3.79907e-2	9.20587e-1
10	3.67643e-2	9.20016e-1	3.16074e-2	9.31305e-1	4.75856e-2	9.02232e-1
15	4.10012e-2	9.12359e-1	4.36882e-2	9.08053e-1	3.10425e-2	9.31207e-1

From the results, it can be seen that using Scale Conjugate Gradient (SCG) with 10 Hidden Node neurones gives a better result in terms of regression value (0.9313) and lower MSE of 0.03161 as compared to other models as shown in Figure 4.

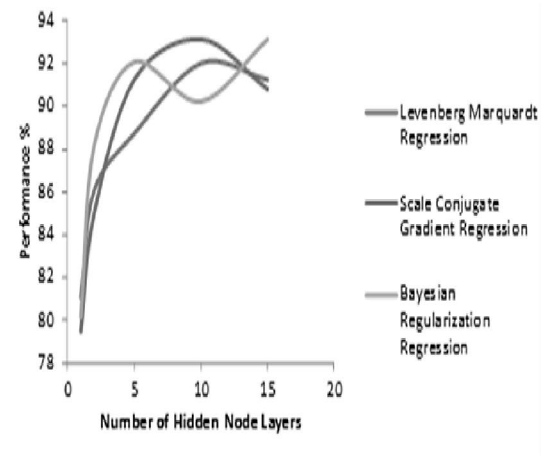


Figure 4: Performance Comparison of Training Algorithms

3.2 MODEL ADOPTION AND TESTING

The model trained with SCG algorithm which produced the best results was adopted and used to predict user behavior for the testing data. Figure 6 show the testing results with a regression value of 0.92309 which is a good prediction rate.

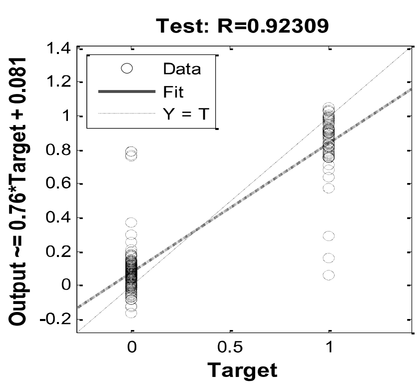


Figure 6: Testing Regression Graph for Model Two.

Table 3 shows the comparison of the desired output versus the predicted output results of the model for the test dataset.

TABLE 3: THE DESIRED OUTPUTS VERSUS PREDICTED OUTPUTS

Desired output			Predicted output		
Lighting point	**Fridge**	**Heater**	**Lighting point**	**Fridge**	**Heater**
0	0	0	0.037	0.056	0.108
0	0	0	0.040	0.055	0.111
0	0	0	-0.056	0.148	0.118
0	0	0	0.145	-0.057	0.071
0	0	0	0.138	-0.050	0.067
0	0	0	0.127	-0.037	0.067
0	0	0	0.113	-0.020	0.056
0	0	0	0.107	-0.013	0.053
0	0	0	0.097	-0.004	0.055
0	0	0	0.084	0.010	0.045
0	0	0	0.079	0.015	0.044
0	0	0	0.072	0.023	0.048
0	0	0	0.061	0.033	0.040
0	0	0	0.824	-0.058	0.102
1	0	0	0.876	-0.067	0.211
1	0	0	0.870	-0.065	0.200
1	0	0	0.866	-0.063	0.193
1	0	0	0.165	-0.113	0.938
0	0	1	0.303	0.094	0.981
0	0	1	0.302	0.095	0.983
0	0	1	1.027	0.018	0.738
1	0	1	0.981	0.079	0.633

The result shows near accurate prediction for users' pattern with minimal error for all the selected devices. This means that, the model performance is satisfactory.

4 CONCLUSION

The understanding of user-appliances interaction pattern is essential for intelligent electrical energy management in order to avoid wastage, fire out-breaks and cost of billing. This research work developed an intelligent ANN based pattern recognition model that learns user interactive pattern with some selected electrical appliances. The purpose of developing this model is to solve the problem of inefficiency in controlling these appliances remotely by either GSM or sensor based techniques. Selecting the best ANN design parameters are always done using trial and error, hence, in this work the best ANN parameters to be adopted was investigated. The developed model was implemented and demonstrated using artificial neural network and Simulink tool boxes in MATLAB R2015(a). The performance of the developed model was evaluated using MSE and R performance metrics. From the results, it was observed that for ten (10) hidden neurones using Scale Conjugate Gradient (SCG) algorithm gave better results in terms of the R value and MSE, therefore was adopted to design the model to control the selected devices. The adopted model with the best parameters was used to test unseen data. A good model performance was achieved with $R = 0.92309$ and $MSE = 0.038589$. The results imply that the developed model can be used for real time control when deployed. Also, SCG algorithm should also be used because of its high performance for pattern recognition problems.

Although this proposed model proves effective, for future works, it is recommended that a real time deployment be carried out using Simulink model and subsequently transferred to hardware for real-time monitoring and control of more electrical appliances in other to minimize fire incidents and over billing. Also, the data collection should be automated and continuous as user behaviours changes over time.

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