



Artificial Neural Network Power Demand Forecasting Model for Energy Management a Case Study of Kabarak University.

Francis Komen¹, Moses Thiga², Peter Rugiri³

¹Kabarak University P.O. Box Private Bag, Kabarak, 20157, Kenya

[Tel:+254 721 327 274](tel:+254721327274), Email: fkomen@kabarak.ac.ke

[Tel:+254 720 780 468](tel:+254720780468), Email: mthiga@kabarak.ac.ke

[Tel:+254 722 691 163](tel:+254722691163), Email: PRugiri@kabarak.ac.ke

Abstract

World governments face challenges of increasing rate of power consumption and energy insecurity. There is need for countries to increase supply sustainability by reduction of demand through energy efficient investments. Load forecasting is important in electric power industry. It provides future load demand information necessary for improving decision making thus enhancing reduction of power demand. Currently many world organizations depend on technical expert's knowledge and experience to assess, evaluate and advice on energy conservation and efficiency status. These methods suffer from inaccuracies and biasness leading to uncertainty in power generation, supply and high costs of energy. The current adoption and advancement of information technology, application of machines learning and artificial intelligence techniques will provide unbiased and more accurate information on energy efficiency status. The research study developed an Artificial Neural Networks Based Power Demand Forecasting Model for Energy Management (ANNPDFMEM). A Multi-Layer Feed Forward Neural Networks structure was used. The electricity load data was collected from the Kenya Power and Lighting company (KPLC) smart meters for Kabarak University in Nakuru County. The collected data set was divided into 70% training set, 15% validation set and 15% testing set. The model was trained using the Back-Propagation learning algorithm. The smallest Mean Square Error in the training iteration is selected and validated with independent set of test samples. Actual smart meter load data from KPLC was compared against the predicted load. The performance evaluation of the model was done to predict the actual load values. The results obtained a Mean Squared Error (MSE) of 9.5%, and R value of 1. The results indicated high accuracy forming the basis for recommendation for adoption of the (ANNPDFMEM) as a tool for future power demand information. This information platform is important for decision making on energy efficiency and conservation strategies for sustainability and energy management.

Keywords: Load Forecasting, energy demand, Energy management, Energy efficiency, Artificial Neural Network, Demand Response.

1. Introduction

In Kenya the effective power generation capacity as at the end of December 2018 is 2,200 megawatts (MW) while demand is at 1,859MW (ERC, 2018). There is insufficient spinning reserve which is a risk to power reliability on the interconnected system which may cause a total system collapse (black outs). The Kenya energy act No. 1 of 2019 section 200 (h), 202 (1) on establishment of energy consumption benchmarks requires power consumers to monitor energy consumption in buildings and to implement measures to reduce energy consumption to acceptable levels. Kenyan gazette notice on Energy management Regulations 2012 requires consumers consuming more than 15,000 Kilowatt-



hours (KWH) of monthly electricity to put in place measures to reduce their consumption by 50%. The affected facilities are among commercial buildings, hotels, institutions and industries. (Ngila & Group, 2015).

Currently the power consumers know their consumption status based on the monthly electricity bills. This data does not give a clear picture of future consumption trends that can enable power reduction decisions. The problem is inability to anticipate future demand with high accuracy. There are few studies that have developed simple, elaborate and accurate load forecasting model. Power consumers therefore need to evaluate and know their consumption behaviour based on historical data in order to effectively manage their power consumption. This can be achieved through power demand forecast. The forecast output will help in, power system planning, energy efficiency management and ensuring good quality of life. This forms a basis for the study and development of an artificial intelligence model to Power Demand Forecasting. A month a-head load demand forecasts will provide decision support. Future load prediction will enable the power system operators ensure an equilibrium between energy demand and electricity supply.

A case study of Kabarak University, where over a million shillings is spent monthly on electric energy bills. This study area is chosen because it is a designated consumer institution by the regulatory authority under section 187-188 of the energy act 2019 (Oyedepo, 2019). The University management has instituted an Energy management committee whose mandate is to develop a university energy policy. The goal is to improve implementation energy efficiency and conservation programs for university sustainability. It endeavours to plan energy saving strategies, monitor energy consumption and implement measures to reduce consumption within the University. This will lead to KABU earning compliance to Energy Act No.1 of 2019 sections (200-205) of Kenya published in 12th March 2019. The institution currently uses the expert knowledge in planning and implementation of energy efficiency and power reliability measures. Therefore, there is need for load forecasting information to enable the institution make energy saving decisions based on information.

2. The Problem

Electric energy being enabler to sustainable development goals calls for a stable, reliable and affordable power supply. There is a rising concern over inefficiency and reliability of power supply in Kenya. The erratic power consumption is causing a challenge in ensuring efficiency and reliability of power supply. To reduce this power inefficiency and improve reliability, ERC has set policy regulations on demand reduction targets for large power consumers. Kabarak University (KABU) is among large power consumers earmarked by the current Energy and Petroleum Regulatory Authority (EPRA). Its average consumption both high rate and low rate is 35,000 Kilowatt-hours (KWH) translating to over one Million shillings monthly.

The Energy regulator expects that this category of consumers shall comply with the Energy Policy Act. It is a regulatory requirement for consumers to earn compliance through implementation of energy saving measures by cutting down its current consumption by 50% according Energy Act published in March 2019. KABU management has made commitment to improve energy efficiency for University sustainability and compliance to these energy regulations through the University energy policy. However, it lacks a tool that can provide information about future consumption critical for making informed decisions on ways to reduce their consumption and energy management. Knowledge of prior load



demand patterns will enable power consumers make strategic planning on implementation of energy reduction measures.

Therefore, this research addressed this problem by designing Artificial Neural Network Based Power Demand Forecasting Model for Energy Management (ANNPDFMEM). The purpose of ANNPDFMEM has been achieved by forecasting electricity demand for one day up to one week ahead. Thus, enables the power consumers to use this information for decision making on; planning, demand reduction strategies, energy management and ensuring good quality of life.

3. Objectives

The main objective of this research study is to develop an Artificial Neural Networks Based Power Demand Forecasting Model for Energy Management a case of Kabarak University. The model will provide a solution to power consumption monitoring and prediction of one day a-head power demand. The specific objectives contributing to this objective are;

- To design an Artificial Neural Networks Based Power Demand Forecasting Model for Energy Management.
- To implement an Artificial Neural Network Based Power Demand Forecasting Model for Energy Management.
- To evaluate the accuracy of the Artificial Neural Networks Based Power Demand Forecasting Model for Energy Management.

4. Literature Review.

4.1 Power Demand forecasting.

Power Demand Forecasting is categorized into three types based on period of time. Short term forecast are load predictions ranging from few minutes to hours up to one week (Barbieri, Rajakaruma et al. 2017). Medium Term Load Forecasts range from one week to one year period (Ahmad and Chen 2018). Long term Forecasting are predictions that range from one year and beyond (Carcedo and Garcia 2017). This load demand information is used as baselines in decision making for energy management. It is important in balancing electricity generation with its demand for maximum efficiency and power reliability. Power consumers use their demand forecasting information to plan for energy conservation measures that lead to reduction of energy consumption and increasing energy efficiency (Barbieri, Rajakaruma et al. 2017).

A study on weather sensitive demand model was developed for small utilities in North Cyprus. It is showed that independent variables including price of electricity, number of customers, tourists and population are significant in estimating the future peak demand of electricity (Mirlatifi 2015). Researchers have also forecasted the demand for electricity using approaches such as Adaptive Neuro Fuzzy Inference System (ANFIS) for prediction of electricity demand in India for the period during 2013 to 2020 (Saravanan, Kannan et al. 2015). Artificial Neural Network (ANN) was applied for forecasting a day ahead electricity price in Spain (Panapakidis and Dagoumas 2016). Decision Support System (DSS) has been utilized for taking decision in a competitive electricity market based on various factors, Hybrid Model used for forecasting electricity demand in china for the period 2016-2020 (Liang and Liang 2017)

A study that made a forecast on the World's green energy demand up to the year 2050 used a feed forward back propagation ANN technique, results showed lower errors and better performance (K. Ermis, 2007). Bilgili in his study applied ANN, Linear Regression

(LR) and Non Linear Regression (NLR) to forecast electricity demand for residential and industrial sector of Turkey. Results were compared between the ANN, LR and NLR showed actual data and the predicted results were almost the same, also the performance values of the ANN method were better than performance values of the LR and NLR models. A study by Adams built econometric model of the Chinese energy economy, it forecasted Chinese energy demand and imports up to 2020, ANN showed superior results (G. Adams and Y. Shachmurove, 2008). Kialaskaki and Reisel developed a model for energy demand forecasting for United States, they compared results from Multiple Linear Regression Models and ANN models, ANN was chosen based on the good ANN model evaluation parameter (Reisel, 2014)

5. Results

5.1 Design of ANNBPDFMEM;

The model design process systematically followed a design science approach of five steps as collecting power consumption data, pre-processing data, building the forecasting network model, training the model and finally testing the model. A feed forward artificial neural network structure was designed because it had a good ability to map nonlinear functions (Taravat, 2015)

5.2. Data collection and pre-processing process;

Kabarak University electricity consumption data was collected from Kenya Power and lighting Nakuru. Historical power consumption for the period January to June 2019 data and current data for the period July -August 2019. The hourly active power in kilowatts (KW), Daily total energy consumption measured in KiloWatts-Hour (KWH) was collected and stored in excel file format. Hourly temperature in degrees Celsius data was collected from Nakuru meteorological station and stored in spread sheets. Data was pre-processed using the mapminmax function in MatLab toolbox. Data was normalized and randomized before presenting to the model network. The input vector was normalized so as to be in acceptable standard range. The output vector was be normalized into its original format.

5.3 Design of model network

We chose to design a multilayer neural network with three layers. The first layer had four input parameters, the hidden layer to have 10 neurons and the output layer to have one output neuron. A sigmoid symmetric transfer function was used on the output. The model structure is as on the figure 1:

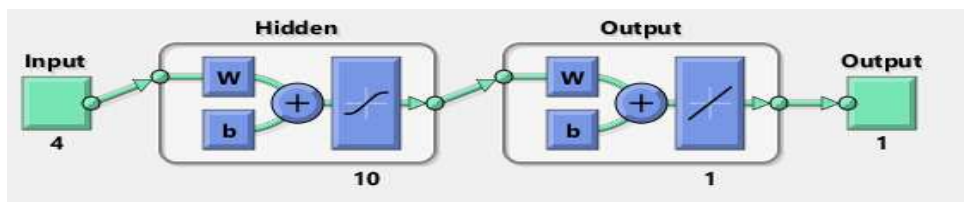


Figure 1: Artificial Neural Network Structure (Matlab, 2018a)

5.4 Model network training.

In this process a number of iterations were done to come up with the most accurate model for demand forecasting. Back-Propagation training algorithm method was used since it had proven effective results and accuracy needed for the network (Hanan A. Akar a. F., 2016).

A delta learning rule was used in this study. The acquired data set was split into the Training set and testing set. Training was the process of adjusting the weights of the neuron to the desired accuracy. The training set was 70%, 15% and 15% testing set. The best model had a network structure of four input neurons, hidden layer neurons, one output neuron.

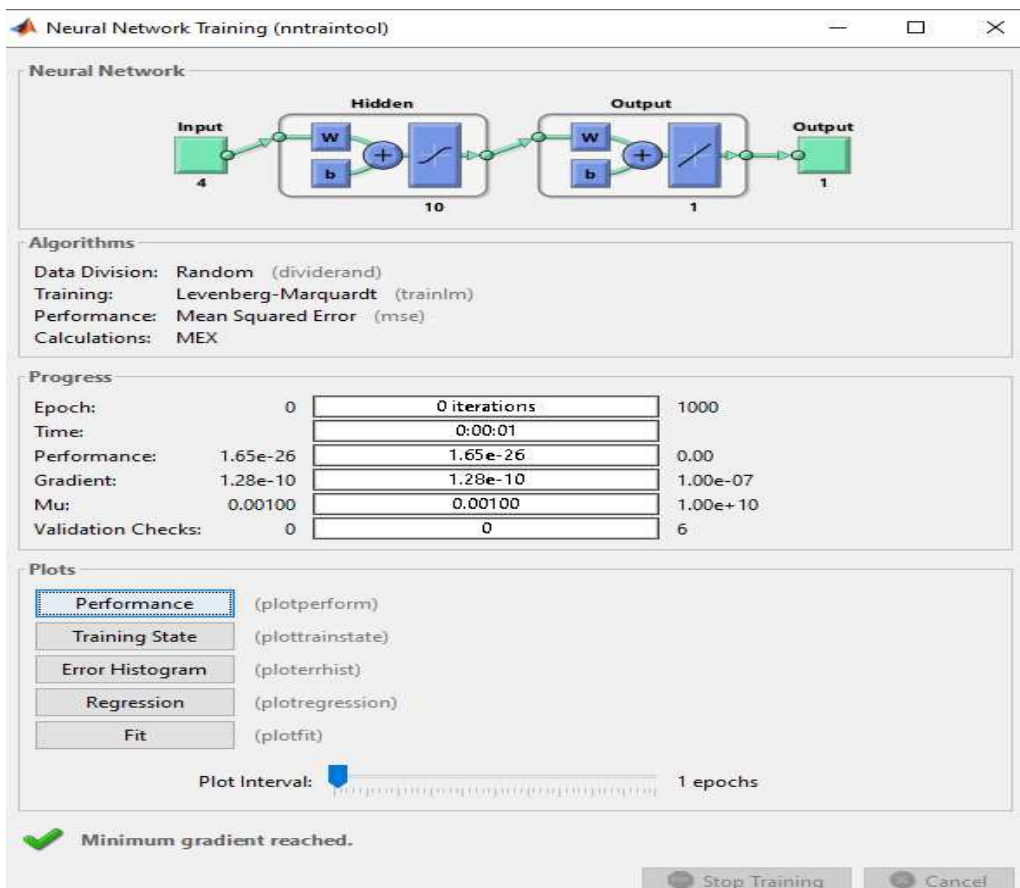


Figure 2: model training window.

Training Algorithm results table 1

	Samples number	Network structure	Levenberg-Marquardt training Algorithm.		Bayesian Regularization Algorithm		Scaled Conjugate function Algorithm	
			MSE	R Value	MSE	R Value	MSE	R Value
Model 1								
Training	1534	[4 6 1]	59314.51	0.812	48536.73	0.855	61243.11	0.813
validation	331	[4 6 1]	59072.94	0.820	0.00	0.855	66336.83	0.808
Testing	331	[4 6 1]	78849.72	0.811	50221.43	0.858	73567.84	0.769
Model 3								
Training	1534	[4 20 1]	33518.16	0.905	33517.62	0.904	56021.43	0.826
validation	331	[4 20 1]	40890.87	0.849	-	-	56495.72	0.838
Testing	331	[4 20 1]	42537.20	0.884	31882.70	0.904	67646.72	0.809



Model 4								
Training	50	[4 10 1]	9.5138	0.999	2.23	0.970	709.78	0.979
Validation	11	[4 10 1]	501.24	0.994	0.00	0.000	341.34	0.904
Testing	11	[4 28 1]	11.47	0.999	2.06	0.899	1348.45	0.924

Table 1: Table showing training algorithm results

It was observed that Levenberg-Marquardt had the best training algorithm as from table 1. Mean squared Error is the defined as the squared difference between outputs and targets. The best was model 7 with lower values which is desirable. Zero values indicate no error. Regression R values is a measure of how close the correlation between output and targets, the model achieved an R value of 1 indicating a close relationship among variables while R value of zero indicates a random relationship.

5.5 Model evaluation.

The trained ANNBPDFMEM model was tested against unseen data for the period 1st August, 2019. The model posted good prediction accuracy when compared with the actual values. The ANNBPDFMEM evaluation showed the following results train performance of 2.9985, Validation performance of 9.39998 and test performance of 9.399. This showed the model is good for prediction with accuracy.

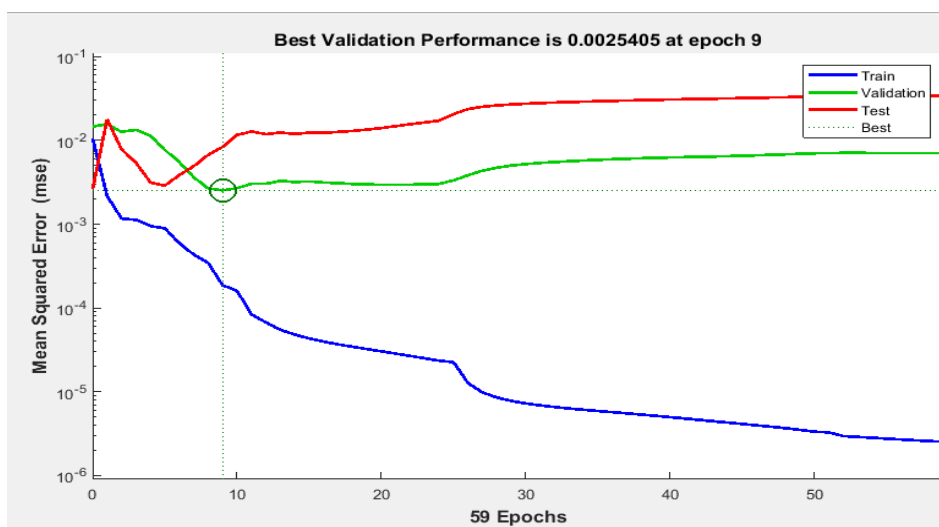


Figure 3: Model evaluation.

We observed that the ANNBPDFMEM achieved best validations at after nine training iterations. From figure 4 below we observed that KABU consumption is high during weekdays as compared to weekends. Also high consumption is witnessed during mid day and evening due to optimum operation activity e.g computer lab operation and lighting

loads.

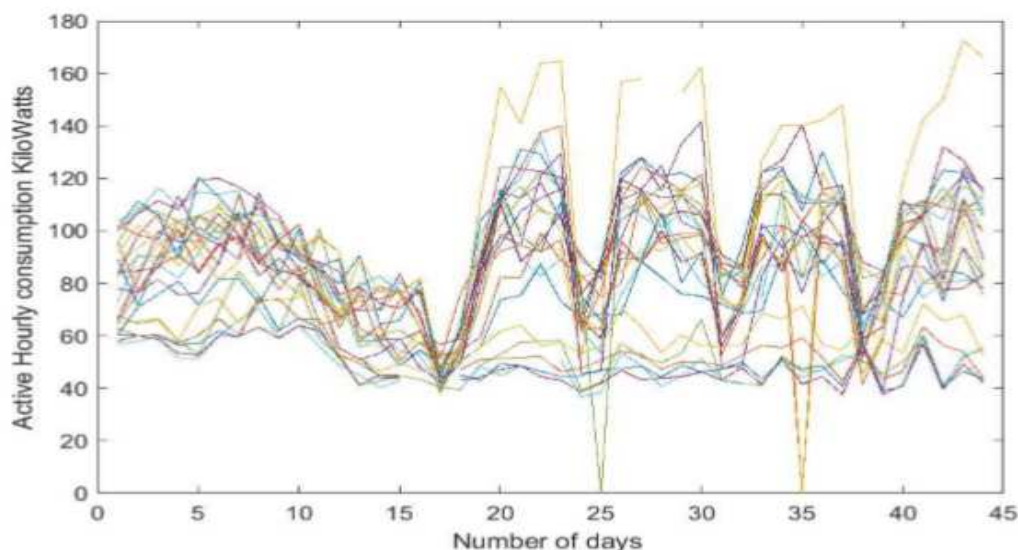


Figure 4 consumption loads analysis evaluation plot.

6. Results.

The model was designed and trained using Kabarak University electricity consumption data. It was observed that Levenberg training algorithm was the best with a MSE of 9.5 with an R value of 1 as from table 1. A network structure with smaller samples of training data proved to train well as compared with large data sample set. The developed model showed that a Forward Neural Network layer used in this study with a BP training algorithm is able to learn well and can be used for forecasting.

The KPLC smart meter measured load data for Kabarak University was compared with the model predicted load table 2. It is seen that the model prediction is close to the actual load with 0.11% Mean absolute percentage error.

Date	Actual load (Mwh)	Predicted load (Mwh)
2019-08-14 12:00:00	1.43068	1.61195
2019-08-13 12:00:00	1.90032	1.92356
2019-08-12 12:00:00	1.97488	2.24838
2019-08-11 12:00:00	2.06650	1.09758
2019-08-10 12:00:00	2.06650	1.28328
2019-08-09 12:00:00	2.08826	1.78486

Table 2: Load forecast results.

$$MAPE = \left(\frac{\text{sum of Actual} - \text{Sum of predicted}}{\text{Total Actual}} \right) / \text{Duration} = 0.11\%$$

6.1 challenges in power demand forecasting.

The challenges of power fluctuations and blackouts deteriorates the forecasting accuracy of the model, this will be mitigated by normalization of raw data.



7. Recommendations and areas of further study.

7.1 Recommendations

The forecasting in future should focus on additional parameters to improve on the model accuracy and provide more information on power demand trends.

7.2 This research area presents a gap which needs further research on effects of student school days on institutional power demand to provide more insights on improving energy efficiency and conservation. This will provide information for decision making on improved energy management.

8. Conclusion.

Artificial Neural Networks power demand forecasting model proof to accurately predict a day a-head power demand. Institutions of higher learning will benefit in adoption of this study by way of prediction of their short-term power demand and use the power consumption information to make informative decisions to reduce consumption and hence cutting down their power bills.

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