Short Term Load Forecasting Using Artificial Neural Networks

Ireri T. Gichovi, Daniel K. Murage and Nicodemus Abungu

***Abstract*—** Load forecasting refers to the prediction of future load conditions based on present or historical data. This is important especially for transmission planning and economic dispatch. In this paper, an Artificial Neural Network (ANN) is trained using historical data for a sub-station at Ruiru, Kenya and the corresponding loading conditions for the sub-station are used to test its accuracy in forecasting the electrical load when given other parameters.

***Keywords*—** ANN, Load Forecasting.

I. INTRODUCTION

The main objective of load forecast studies is to predict the amount and nature of electrical load that can be expected at a specified future time on a particular bus or system. This information is important in economic dispatch calculations and unit commitment studies.

Long term load forecasting is mainly used when seasonal variations are considered or when planning for new generating stations, sub-stations and transmission lines while short term load forecasting is particularly useful in regional control for unit commitment and economic dispatch.

Conventional methods used in load forecasting employ statistical techniques like regression analysis [1-3]. Their main drawback is the time it takes to compute them since several load forecasts may be required on an hourly, daily or weekly basis. With the advent of artificial intelligence, in recent years, expert systems, pattern recognition, decision tree, neural networks and fuzzy logic methodologies have been applied to many power system problems.

In this paper, 7 mutually exclusive variables are chosen to represent conditions which may be used to forecast the load [14]. They form the input variables for the neural network. The corresponding load at the Ruiru sub-station forms the target variable for training the network. The artificial neural network is then trained using the Leven-Marqudat algorithm and validated and tested using sample conditions and loads from the same substation.

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II. METHODOLOGY

To perform the load forecasts, the use of the Artificial Neural Network was aimed at having the network identify the main relations that exist between factors that affect the load and the resulting load from historical data. Once this relationship was identified, it could then be used to train the ANN and the trained network would then be used to forecast future load conditions preemptively.

A. INPUT VARIABLE SELECTION

The output variable was the maximum loading condition for each day for 702 days. A range of variables that possibly affect the load were identified but they had to be narrowed down to a limited number so as to reduce the computational requirement of training the ANN and also reduce its size to enable faster load forecasting. The selected variables for training the ANN based on historical experience were:

i. Month of the year
ii. Day of the week
iii. Special days or holidays
iv. Gross Domestic Product
v. Population
vi. Temperature
vii. Rain or precipitation

B. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks have been in use for a few years now in power systems problems including stability analysis [4-13]. This artificial intelligence method is based on an interconnection of artificial neurons that have a structure similar to the biological neuron.

The artificial neurons have several inputs that are aggregated at an adder stage where the values from the various inputs are multiplied by an input weight depending on the influence they have on the desired target output. After the adder stage, the aggregated signal is the passed through an activation function. The activation function depends on the relationship between the inputs and outputs.

Depending on the complexity of the problem under study, a number of artificial neurons are arranged successively to form the ANN. It has several neurons in parallel in 3 main layers: Input Layer, Hidden Layer and Output Layer. The input layer accepts the input variables, processes them and passes them

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on to the hidden layer. The hidden layer can have as many neurons as the problem requires and simply provides a means to adjust more weights in the input layer so as to have more sensitivity on the output to individual inputs. The output layer usually has one neuron and aggregates the outputs from the hidden layer to the single output.

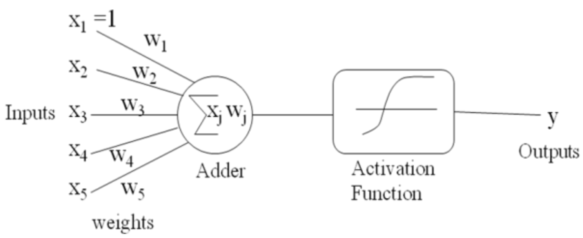

Fig. 1: Artificial Neuron

C. SUPERVISED TRAINING

In training the ANN, two main methods exist: Supervised and Unsupervised training.

In unsupervised training, the inputs are known and the exact relationship between the inputs and the outputs may be known from past experience but the output is unknown. The network is then created with known input weights and activation functions. From these variables, the output is then generated from the already constructed network.

In supervised training, a set of input and output variables exists but the main relationships between the two sets of variables is unknown. Each set has a corresponding output to each of the input variable set. These variable sets are fed into a 'blank' neural network and the network adjusts itself during the training phase. When a new set of input-output pair is fed into the network, the network adjusts its weights accordingly but the error from previous input-output pairs is factored in through a process called back-propagation. After all the input-output pair sets have been fed through the network, the resulting neural network is the aggregate of all of them and now represents the relationship between the input and output variables. It can then be used to predict future outputs given a set of input variables.

D. NETWORK TRAINING

For the study, the seven set of input variables were the inputs while the recorded load in kilowatts was the output. An initial network was designed with one neuron in the input layer, one in the output layer and 10 in the hidden layer. An initial input-output set of 100 samples was used in the training. The training was done using the nftool in MATLAB. 70% of the sample was used in training, 15% in validation of the network model and yet a further 15% in testing the model. The resultant network was then used to predict the loading against 702 days whose actual loading was known. The error between the load predicted by the neural network and the actual loading recorded was then calculated and the average error calculated.

To evaluate the most suitable network configuration, the number of neurons in the hidden layer was increased in steps of 10 neurons up to 100 neurons. To also investigate the effect of the sample size, the input-output pairs used for training was increased from 100 to 1500 in steps of 100 for each size of layer. A uniform sample data set of 702 samples was used to test the resulting networks.

III. RESULTS AND DISCUSION

The first network with 10 neurons in the hidden layer yielded the results as shown in Table 1 below

10 NEURONS		
SAMPLES	**AVERAGE ERROR**	**% ERROR**
	kW	**%**
100	-13835.7	177.1
200	-514.4	10.5
300	740.6	13.6
400	420.3	12.9
500	386.3	8.1
600	-53.1	5.0
700	362.5	6.9
800	220.1	6.9
900	64.0	2.8
1000	41.7	5.3
1100	-3.2	4.7
1200	6.1	3.1
1300	76.3	6.0
1400	-6.9	3.2
1500	20.4	5.0

Table 1: 10 Neuron Hidden layer network performance

From table 1, it is seen that low samples used in training yield poor results with more than 100% error for 100sample training set.

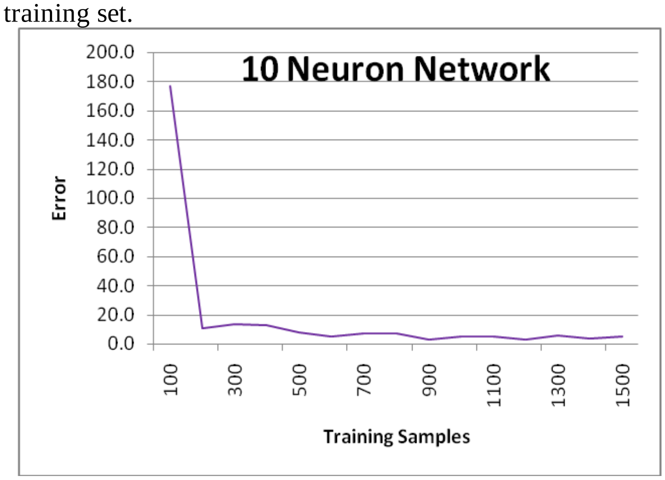

Fig. 2: Error from 10 Neuron Network vs. Sample size

The accuracy of the network in predicting the load improved with increased training data sets as seen in Fig. 2 but saturation effects seem to kick in past 900 samples when the error begins to fluctuate but still within 10% margin of error.

The saturation effects of sample size seemed to be of importance in determining the size of the network and so the increase in the network model to accommodate more neurons in the hidden layer was implemented in stages of 10 neurons with a sample of the results shown below;

40 NEURONS		
SAMPLES	AVERAGE ERROR	% ERROR
	kW	%
100	45541.3	586.9
200	-4899.5	101.3
300	-11002.4	146.0
400	2515.2	96.5
500	550.5	16.8
600	167.2	9.1
700	262.3	7.6
800	90.6	5.7
900	-15.9	6.6
1000	50.5	5.5
1100	174.5	7.6
1200	101.7	3.0
1300	-260.6	6.2
1400	104.1	6.0
1500	-266.4	8.6

Table 2: 40 Neuron Hidden layer network performance

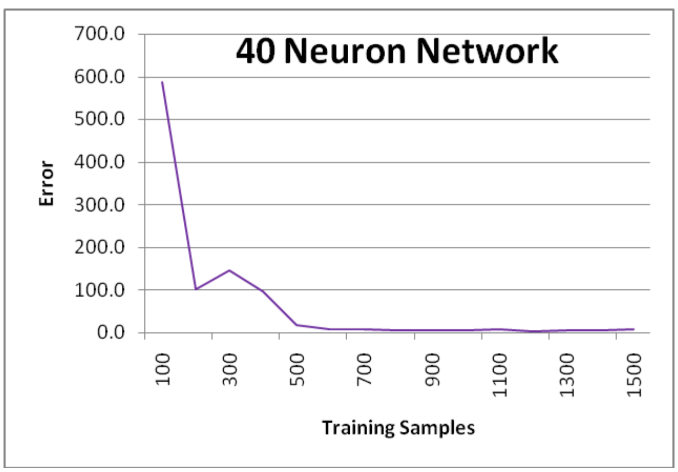

Fig. 3: Error from 40 Neuron Network vs. Sample size

The lowest error is now 3% at 1200 samples. This can be explained by the incresed number of neurons in the hidden layer which delay saturation effects. Also important is the increased error at 100 samples as the information may not be enough to fully adjust weights in the hidden layer.

Looking at 70 neurons in the hidden layer the results were;

70 NEURONS		
SAMPLES	AVERAGE ERROR	% ERROR
	kW	%
100	32718.0	442.8
200	-40835.1	571.6
300	16467.4	418.5
400	3206.8	95.4
500	1880.0	27.7
600	-298.0	12.9
700	774.8	15.4
800	-56.0	8.9
900	57.8	2.6
1000	-351.1	12.1
1100	-1646.2	26.5
1200	-58.3	4.2
1300	46.1	7.6
1400	-18.4	7.0
1500	777.3	14.6

Table 3: 70 Neuron Hidden layer network performance

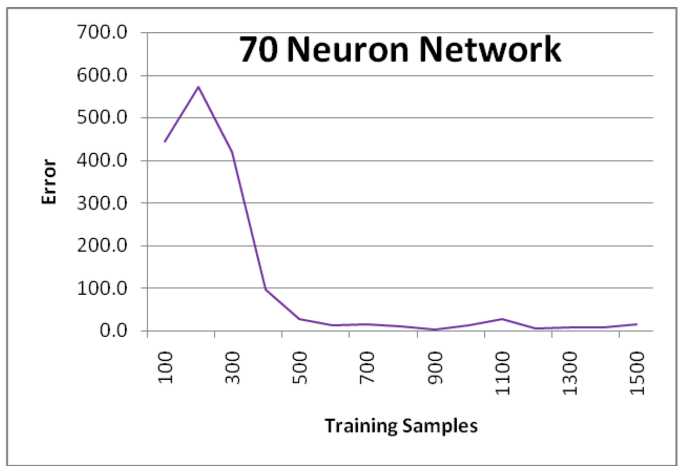

Fig. 4: Error from 70 Neuron Network vs. Sample size

Again, the minimum error is at 900 neurons, similar to the 10 neuron network. However, a few salient features arise. A spike in the error is observed at about 1100 samples, similar to another in the 40 neuron network which was much smaller. Also, the error magnitude rises initially before settling, an indication that smaller networks may not be showing this feature but it may well exist inherently. The implication is an indication larger networks may not even be fully trained when using small data sets and an error spike occurs when all neurons are initially trained.

100 NEURONS		
SAMPLES	AVERAGE ERROR	% ERROR
	kW	%
100	-7576.9	683.5
200	-21910.0	504.7
300	-63518.0	786.9
400	3122.1	116.5
500	-7189.7	105.4
600	2.9	35.8
700	-11.1	9.5
800	53.7	8.4
900	-144.9	13.4
1000	-206.1	10.3
1100	1135.3	16.9
1200	180.4	3.6
1300	229.9	3.9
1400	1055.1	19.3
1500	52.9	4.0

Table 4: 100 Neuron Hidden layer network performance

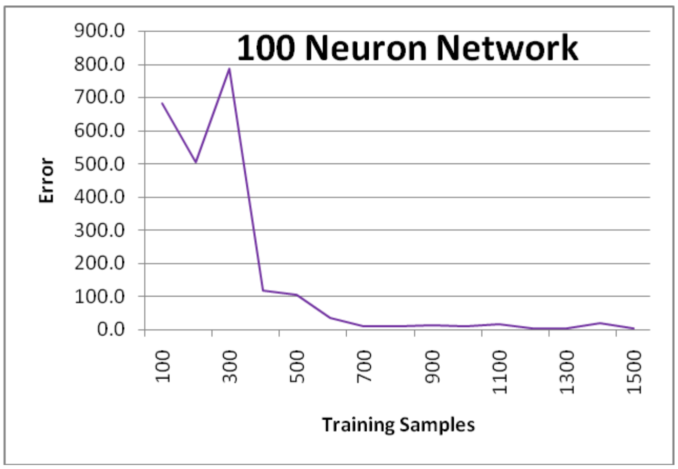

Fig. 5: Error from 100 Neuron Network vs. Sample size

For the 100 neuron network, all the features from the other networks are seen. Additionally, the spike at 1100 samples is replicated at 1400 samples while the lower sample values have very erratic error variations. It can still however be noted that the minimum error recorded here is 3.6% at 1200 neurons.

To study trends in maximum and minimum error values, the full table for error variation with sample size and network size is given in Appendix 1. The resulting error plots are shown in Fig. 6.

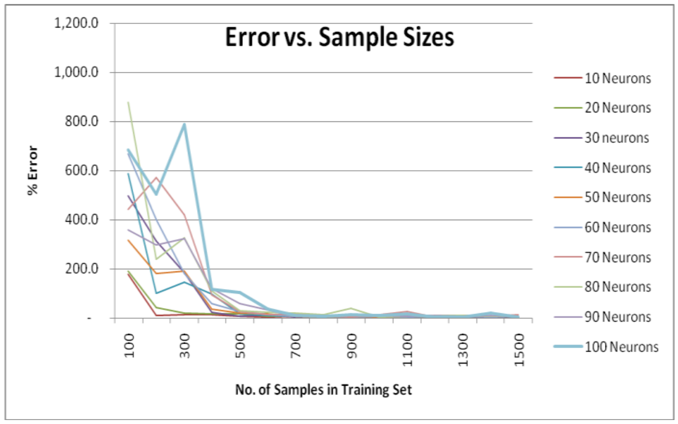

Fig. 6: Error vs. Sample Sizes for all network sizes

From Fig. 6, it is clear that lower sample sizes give much greater errors that are simply incorrect. However, as the sample size increases, it becomes easier to predict the load and minimum error values occur at between 800 samples and 1200 samples depending on the network size.

Similarly, the minimum error as seen from Appendix 1 is consistently below 5% save for the network with 90 neurons where it is at 6.4%. This indicates 95% accuracy in load prediction, which is fairly good for short term load forecasting.

IV. CONCLUSION

It can be seen that load forecasting was done using the artificial neural network and the accuracy investigated. From the results, the load forecast should be done using a network fine tuned to the data set. The selected variables should have been recorded in advance to train the network. Historical data in this case represents load changes for the given load centre and forms the training sample data sets. Over time, this data grows and can be used to further train the network, allowing for greater accuracy.

Moving forward, the sensitivity of each network size to sample size need to be investigated so as to clearly determine the optimum network size given a particular sample size. Similarly, the sensitivity of the forecast load to each of the particular input factors should be investigated to determine the most critical and perhaps even add other factors not captured in this study.

APPENDIX

NEURONS	10	20	30	40	50	60	70	80	90	100
SAMPLES										
100	177.1	192.3	496.2	586.9	317.7	669.5	442.8	879.2	358.0	683.5
200	10.5	43.3	314.9	101.3	182.7	402.0	571.6	239.0	295.8	504.7
300	13.6	20.5	184.3	146.0	191.7	181.0	418.5	327.8	323.7	786.9
400	12.9	15.8	22.9	96.5	37.2	59.0	95.4	111.5	118.4	116.5
500	8.1	15.2	6.6	16.8	21.2	26.6	27.7	28.7	57.3	105.4
600	5.0	6.9	13.9	9.1	15.9	12.7	12.9	23.3	31.5	35.8
700	6.9	5.8	3.2	7.6	7.3	8.0	15.4	20.2	7.5	9.5
800	6.9	5.5	6.1	5.7	2.8	7.9	8.9	14.4	11.0	8.4
900	2.8	5.4	7.2	6.6	6.6	3.9	2.6	38.8	11.8	13.4
1000	5.3	5.0	5.2	5.5	2.8	8.0	12.1	4.9	10.9	10.3
1100	4.7	5.5	3.0	7.6	7.2	4.9	26.5	8.4	8.3	16.9
1200	3.1	5.6	5.2	3.0	2.9	6.5	4.2	11.2	11.0	3.6
1300	6.0	6.7	5.6	6.2	10.2	7.2	7.6	10.6	7.1	3.9
1400	3.2	2.8	3.0	6.0	8.0	4.7	7.0	6.9	8.7	19.3
1500	5.0	5.8	5.5	8.6	9.5	7.0	14.6	8.3	6.4	4.0
max	177.1	192.3	496.2	586.9	317.7	669.5	571.6	879.2	358.0	786.9
min	2.8	2.8	3.0	3.0	2.8	3.9	2.6	4.9	6.4	3.6

REFERENCES

[1] I. Morhram, and S. Rahman, "Analysis and Evaluation of Five Short Term Load Forecasting Techniques," IEEE Trans. on Power Systems,vol. 4, No. 4, pp. 1484-1491, October 1989.

[2] H. M. Al-Hamadi, and S. A Soliman, "Long-term/mid-term electric load forecasting based on short-term correlation and annual growth," Electric Power Systems Research, vol. 74, pp. 353-361, 2005.

[3] R.L Sullivan, "Power system Planning",Mcgraw-Hill Book Co.,Nrw York.

[4] J Donald. F. Specht, "Probabilistic neural networks for classification, mapping, or associative memory", Proc. EEE Inf. Conf. Neural Networks, San Diego, CA, VOI. 1, pp. 525-532, July 1988.

[5] Zhang Yun, Zhou Quan, Sun Caixin, Lei Shaolan, Liu Yuming, and Song Yang, "RBF Neural network & ANFIS based short term load forecasting in real time price Environment", IEEE Transactions on Power systems,Vol23,No.3,Aug2008.

[6] ZbigniewGontarand Nikos Hatziargyriou, "Short Term load forecasting using Radial basis neural network", SM, IEEE2001 IEEE Porto Power Tech Conference, September, Porto, Portugal.

[7] S. N. Njoroge and C. M. Muriithi, "Voltage Stability Analysis using CP_ANN and Optimised Capacitor Placement (SRI Conference 2010)," presented at the JKUAT-SRI Conference 2010.

[8] Mohammad Shahedehpour, HatimYamin, ZuliAli : "Market operations in Electric power systems, forecasting scheduling and risk management", IEEE, John Wiley & Sons, Inc., Publication, 2002 .

[9] R.C.Bansal, "Overview and Literature Survey of Artificial Neural Networks Applications to Power Systems (1992-2004)",IE Journal, Vol86, March, 2006.

[10] M.TarafdarHaque, A.M.Kashtiban, "Application of Neural Networks in Power systems: A Review", Proceedings of world Academy of Science and Technology, Vol 6, June 2006

[11] H. S. Hippert, C. E. Pedreira, and R. C. Souza, "Neural Networks for short-term Load Forecasting: A Review and Evaluation," IEEE Trans. on Power Systems, vol. 16, No.1, pp. 44-55, February 2001.

[12] G. Zhang, B. E. Patuwo, and M. Y. Hu, "Forecasting with artificial neural networks: The state of the art," International Journal of Forecasting, vol. 14, pp. 35-62, 1998.

[13] R. Lamedica, A. Prudenzi, M. Sforna, M. Caciotta, V. OrsoliniCencelli, "A Neural Network Based Technique For Short Term Load Forecasting Of Anomalous Load Periods," IEEE Trans. on Power Systems, vol. 11,No. 4, pp. 1749-1756, November 1996

[14] J. W. Taylor, and R. Buizza, "Neural Networks Load forecasting with Weather Ensemble Predictions," IEEE Trans. on Power Systems, vol. 17, pp. 626-632, 2002.