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AN ARTIFICIAL NEURAL NETWORK APPROACH TO SHORT-TERM LOAD FORECASTING FOR NIGERIAN ELECTRICAL POWER NETWORK

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ABSTRACT

Load forecasting is inevitable for electric industry operations nowadays. Factors like energy demand, energy generation, load switching, infrastructure sizing, energy projection and analysis are all effectively handled through load forecasting. If the power generated is insufficient to meet the demand, there arises the problem of epileptic power supply and in case electric power is generated in excess, the power generation industry will have to be responsible for the losses. Load forecasting is therefore a core aspect of electric power industry operations. In this paper, artificial neural network (ANN) technique, which was trained with backward propagation algorithm was used for short-term load-forecasting using data obtained from National Control Centre, Osogbo, Nigeria. The simulation process involves three layers, 80 hidden nodes, hidden layer “logsig” and “tansig” activation functions and “purelin” output activation function. Training goal is set at 4×10^{-9}. Training epoch is set at 1000 and learning rate of 0.1. Results obtained when compared with the field data show a better performance of ANN as a tool for reliable short-term load prediction. This work is intended to be a basis for real forecasting applications that would guarantee profitability of the operations of electric industry in order to attract investors to the power sector.

INTRODUCTION

Electrical power cannot be stored as it must be generated at the moment it is demanded [1]. Hence, the power industries should ensure that the electrical load on their networks be evaluated in advance. This load evaluation before its actual existence is termed load forecasting [2]. Power system expansion planning begins with a forecast of anticipated future load requirements. There is a growing tendency towards unbundling the electricity system [3]. This continually confronts various sectors of the network, such as; generation, transmission, and distribution with increasing demand on planning management and operations of the system [4]. An adequate model for load forecasting is required for planning and operation of an utility industry. Electrical load forecast enables power industry to make decisions on generation and purchase of electrical energy, voltage control, load switching, infrastructure development, and network reconfiguration [5].

To accurately carry out load forecast, historical load plays a vital role alongside the present load in context of realistic modern forecast tool to be applied [6]. In the previous decades, many models were proposed for accurate forecasting of electrical load. Load forecasting is the starting point of network operations and once it is forecasted accurately for each hour of 24 hour a day, then an economic generation planning is made depending on the fuel cost merit of the entire participating network plants [7]. Depending on this economic generation scheduled, generator could be ordered on busbars with enough lead time to meet scheduled forecast. Load is also dispatched in coordinated fashion to enable economic, stable, and qualitative electricity supply.

Accurate model for load forecasting is paramount for planning and operation of any utility industry. Load forecasting enables utility industry to come up with vital decisions which include generation of power. Load forecast is generally grouped into three, which are short term, medium term and long-term load forecasts [8]. With the deepen reform of electricity and generation of power sector in Nigeria, load forecasting has now become very important. A variety of tools could be used, this includes statistical method such as similar day and regression approach, logic expert system, econometric mode, support vector machines, and so on. There are now so many models and techniques that have been used for load forecast and subsequent analysis [9-10].

MATERIAL AND METHODS

Artificial Neural Network Concept

ANN learns the relationship among past, current and future loads and temperatures. It interpolates between the temperature data and load in a training data set in order to give the forecasted load. The structure of information processing system is the key element in ANN. ANN comprises of a great number of highly interconnected processing neurons which work together to proffer solution to specific problems. ANN is configured for specific applications such as data classification or pattern recognition via a learning process. Learning in biological systems entails adjustment to the synaptic connections existing among the neurons. ANN is an information processing paradigm inspired by the way biological nervous systems process information. The novel structure of the information processing system is the key element of this paradigm.

Artificial Neuron

It is a device that has several inputs and a single output and possesses two modes of operation namely; the training and using modes. In the training mode, the neuron is trained to fire or not, for input patterns. In the using mode, when a taught input pattern is detected at the input, its associated output becomes the current output. If the input pattern does not belong in the taught list of input pattern, the firing rule is used to determine whether to fire or not.

Feed-Forward Back-propagation Network

It permits signals to travel only in one direction i.e. from the input to output. There is no feedback, that is, the output of any layer does not affect that same layer. Feed-forward ANNs are straight forward networks associating the inputs with the outputs. The back-propagation neural network is usually a multilayer neural network with the input, hidden and output layers. The output vector is compared to the expected output at the layer's output. If there is no difference, the weights of the connections are left intact, if there is difference, the error is computed from delta ruled given by Eq. 1.

$$dw_{ij} = r \times \left(t_j - y_{js}\right) \tag{1}$$

where,

r = learning rate,
t_j = target output
y_j = actual output

The delta rule change in weight in a way that reduces the error, the differences between the desired and actual outputs. However, it has been revealed that delta rule gives a useful means of modifying the initial weight vectors towards the optimum one and the error is propagated backward via the network. The idea is to tune the weights to reduce the difference between the real and expected outputs in its prediction stage on the training set. A well-trained back propagation network tends to provide sensible results when an input that is totally new is presented. Usually, a new input gives an output for such an input that is supplied to the network.

Back propagation has two distinct phases of the algorithm, the forward and backward phases. In the forward phase, the input is propagated forward, layer by layer which results in the corresponding output. The output is then compared to the desired (target) output and the difference is propagated backwards in the network as an error signal. In the backward phase, the errors at the output are propagated backwards towards the input layer with the partial derivative of the performance with respect to the weight and biases computed for each of the layers.

Error analysis

As the load characteristics change, observation of errors is crucial for forecasting process. The Mean Absolute Percentage Error (MAPE), ε is represented by Eq. 2 and Root Mean Square Error (RMSE), σ is represented by Eq. 3 for "after-the-fact" error analysis.

$$\varepsilon = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|X_t - X_f\right|}{X_t}\times 100 \tag{2}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(X_t - X_f\right)^2} \tag{3}$$

where X_t and X_f are the actual and forecasted loads, respectively.

Back-Propagation Algorithm for this work

The back-propagation algorithm used for the implementation of this work contains the following:

(1) Simulation parameters are supplied;
(2) Select Numbers of layers to be three (3);
(3) Training parameter Goal = 4 x 10-9;
(4) Hidden nodes = 60-80;
(5) Hidden layer activation function = Logsig, Tansig;
(6) Performance function = MAPE;
(7) Learning Rate = 0.1.
(8) Output layer activation function = Purelin;
(9) Epochs = 10000;

The implementation of the back-propagation algorithm is presented in Table 1 to Table 7, all showing the hour, day, actual and predicted loads. These tables are the representations of the days of the week, that is, Sunday to Saturday with the corresponding results obtained and compared appropriately.

RESULTS AND DISCUSSION

Having utilized the procedures enumerated in the above section, results obtained were analyzed and presented in Figure 1 to Figure 7. As could be seen from the obtained results, graphs of actual and forecast load in Megawatts (MW) for each day were plotted against the time in hours. It was observed that the ANN forecast and actual load patterns are almost equal throughout the forecast period. The RMSE was evaluated as 0.51% for the one-week period forecasted. The

forecast curve obtained appeared smoother which indicate easier load transition from one load profile to another. The effect of the forecast curve would result in longevity of power equipment, reduction of power dissipated by switching equipment, lesser noise, lesser downtime, better integration with other artificial intelligence tools, and many more.

Table 1. Monday load outlook per hour

Hour of the day	Day of the week	Actual Load (MW)	Predicted Load (MW)
1	Monday	2881.9	2759.8
2	Monday	2880.4	2734.8
3	Monday	2883.5	2724.8
4	Monday	2803.5	2844.6
5	Monday	2991	2855.2
6	Monday	3016.6	2845
7	Monday	2992.7	2918.1
8	Monday	3083.1	2975.2
9	Monday	3090.6	2867.7
10	Monday	2921	2817.8
11	Monday	3012.1	2832.7
12	Monday	2319.4	2862.3
13	Monday	2398.8	2886.7

14	Monday	2777.3	2888.8
15	Monday	3050.5	2831.8
16	Monday	2995.4	2926.4
17	Monday	3078.7	2933.5
18	Monday	3236.2	3031.1
19	Monday	3340.1	3295
20	Monday	3352.1	3311.5
21	Monday	3372.3	3244.4
22	Monday	3280.7	3276.9
23	Monday	3307.1	3280.7
24	Monday	3087.9	3028.8

Table 2. Tuesday load outlook per hour

Hour of the day	Day of the week	Actual Load (MW)	Predicted Load (MW)
1	Tuesday	3059.0	2881.9
2	Tuesday	3059.3	2880.4
3	Tuesday	3164.4	2883.5
4	Tuesday	3204.7	2803.5
5	Tuesday	3067.7	2991.0
6	Tuesday	3207.6	3016.6
7	Tuesday	3209.6	2992.7
8	Tuesday	3079.9	3083.1
9	Tuesday	3116.9	3090.6
10	Tuesday	3110.6	2921.0
11	Tuesday	3045.1	3012.1
12	Tuesday	2982.2	2319.4
13	Tuesday	3011.3	2398.8
14	Tuesday	3030.3	2777.3
15	Tuesday	2961.1	3050.5
16	Tuesday	3002.9	2995.4
17	Tuesday	3010.8	3078.7
18	Tuesday	3244.3	3236.2
19	Tuesday	3364.1	3340.1
20	Tuesday	3452.9	3352.1
21	Tuesday	3496.1	3372.3
22	Tuesday	3484.5	3280.7
23	Tuesday	3435.4	3307.1
24	Tuesday	3026.1	3087.9

Table 3. Wednesday load outlook per hour

Hour of the day	Day of the week	Actual Load (MW)	Predicted Load (MW)
1	Wednesday	3041.6	3059
2	Wednesday	3058.8	3059.3
3	Wednesday	3073.5	3164.4
4	Wednesday	3095.4	3204.7
5	Wednesday	3185	3067.7
6	Wednesday	3233.3	3207.6
7	Wednesday	3138.2	3209.6
8	Wednesday	3197.1	3079.9
9	Wednesday	3129.8	3116.9
10	Wednesday	3014	3110.6
11	Wednesday	3037.6	3045.1
12	Wednesday	3086	2982.2

13	Wednesday	3033.5	3011.3
14	Wednesday	3036.2	3030.3
15	Wednesday	3029.4	2961.1
16	Wednesday	3052.5	3002.9
17	Wednesday	3133.6	3010.8
18	Wednesday	3129.2	3244.3
19	Wednesday	3316.1	3364.1
20	Wednesday	3470.4	3452.9
21	Wednesday	3490.7	3496.1
22	Wednesday	3466.6	3484.5
23	Wednesday	3265.6	3435.4
24	Wednesday	3052.9	3026.1

Table 4. Thursday load outlook per hour

Hour of the day	Day of the week	Actual Load (MW)	Predicted Load (MW)
1	Thursday	3081.2	3041.6
2	Thursday	3070.3	3058.8
3	Thursday	3065.2	3073.5
4	Thursday	3073.6	3095.4
5	Thursday	3062.6	3185
6	Thursday	3199.4	3233.3
7	Thursday	3157.8	3138.2
8	Thursday	3169	3197.1
9	Thursday	3097.7	3129.8
10	Thursday	3057.1	3014
11	Thursday	2738.9	3037.6
12	Thursday	2891.2	3086
13	Thursday	2939.5	3033.5
14	Thursday	2981.2	3036.2
15	Thursday	3040.2	3029.4
16	Thursday	3093.5	3052.5
17	Thursday	3051.5	3133.6
18	Thursday	3146.7	3129.2
19	Thursday	3305.6	3316.1
20	Thursday	3335.1	3470.4
21	Thursday	3473.7	3490.7
22	Thursday	3599.6	3466.6
23	Thursday	3442.8	3265.6
24	Thursday	3119.4	3052.9

Table 5. Friday load outlook per hour

Hour of the day	Day of the week	Actual Load (MW)	Predicted Load (MW)
1	Friday	3122.9	3081.2
2	Friday	3086.7	3070.3
3	Friday	3063.2	3065.2
4	Friday	3118.7	3073.6
5	Friday	3134.9	3062.6
6	Friday	3110.7	3199.4
7	Friday	3144.6	3157.8
8	Friday	3131.9	3169
9	Friday	3120.4	3097.7
10	Friday	3119.1	3057.1
11	Friday	3019.7	2738.9
12	Friday	3061.9	2891.2

13	Friday	2530.6	2939.5
14	Friday	2773.8	2981.2
15	Friday	2941.1	3040.2
16	Friday	2995.7	3093.5
17	Friday	3008.5	3051.5
18	Friday	3197.5	3146.7
19	Friday	3265.3	3305.6
20	Friday	3322.6	3335.1
21	Friday	3354	3473.7
22	Friday	3570.2	3599.6
23	Friday	3464.2	3442.8
24	Friday	3031.7	3119.4

Table 6. Saturday load outlook per hour

Hour of the day	Day of the week	Actual Load (MW)	Predicted Load (MW)
1	Saturday	3035.6	3122.9
2	Saturday	3054.3	3086.7
3	Saturday	3088.4	3063.2
4	Saturday	3073.3	3118.7
5	Saturday	3074.8	3134.9
6	Saturday	3151.2	3110.7
7	Saturday	3105.1	3144.6
8	Saturday	3120	3131.9
9	Saturday	3072.5	3120.4
10	Saturday	3076.7	3119.1
11	Saturday	3052.1	3019.7
12	Saturday	2985.8	3061.9
13	Saturday	3059.2	2530.6
14	Saturday	3015.7	2773.8
15	Saturday	3030.2	2941.1
16	Saturday	3080.1	2995.7
17	Saturday	3065.8	3008.5
18	Saturday	3132.3	3197.5
19	Saturday	3267.9	3265.3
20	Saturday	3309.8	3322.6
21	Saturday	3312.2	3354
22	Saturday	3376.6	3570.2
23	Saturday	3338.6	3464.2
24	Saturday	3125.6	3031.7

Table 7. Sunday load outlook per hour

Hour of the day	Day of the week	Actual Load (MW)	Predicted Load (MW)
1	Sunday	3039.9	3035.6
2	Sunday	3032	3054.3
3	Sunday	3046.7	3088.4
4	Sunday	3067.1	3073.3
5	Sunday	3062.1	3074.8
6	Sunday	3087.4	3151.2
7	Sunday	3093.3	3105.1
8	Sunday	3063.4	3120
9	Sunday	3041.5	3072.5
10	Sunday	2990.4	3076.7
11	Sunday	2984.6	3052.1
12	Sunday	2991.1	2985.8

13	Sunday	3037.8	3059.2
14	Sunday	2937.8	3015.7
15	Sunday	3001.1	3030.2
16	Sunday	2388.8	3080.1
17	Sunday	2471	3065.8
18	Sunday	2642.4	3132.3
19	Sunday	2688.9	3267.9
20	Sunday	2702.6	3309.8
21	Sunday	2730.5	3312.2
22	Sunday	2875.5	3376.6
23	Sunday	2982.2	3338.6
24	Sunday	2890	3125.6

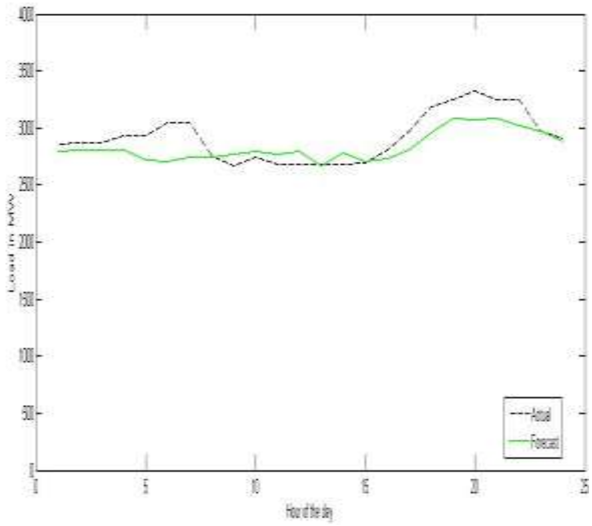

Figure 1: Monday Load Forecast

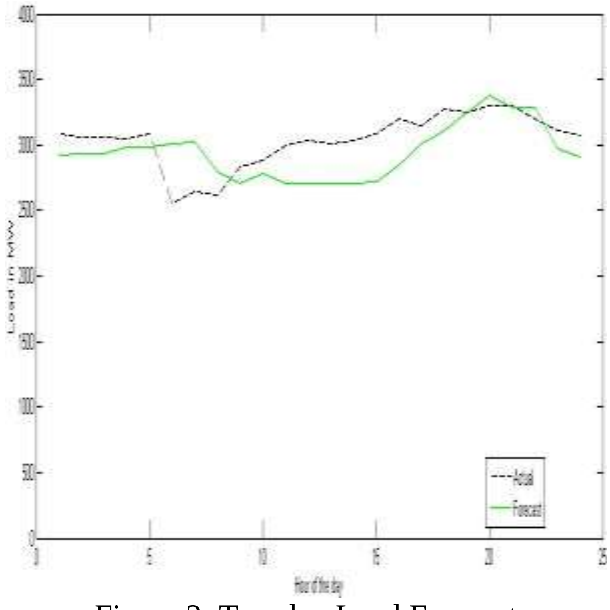

Figure 2: Tuesday Load Forecast

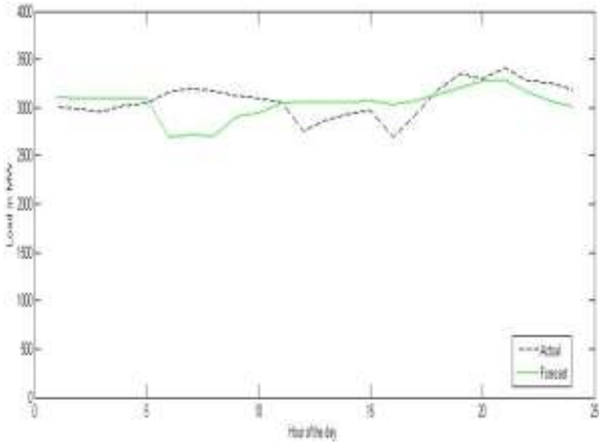

Figure 3: Wednesday Load Forecast

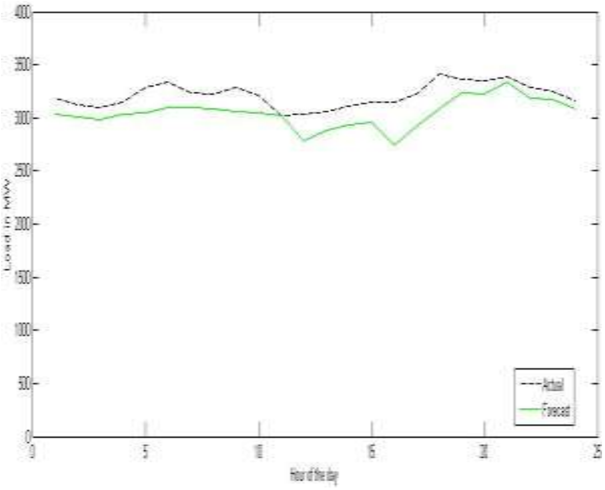

Figure 4: Thursday Load Forecast

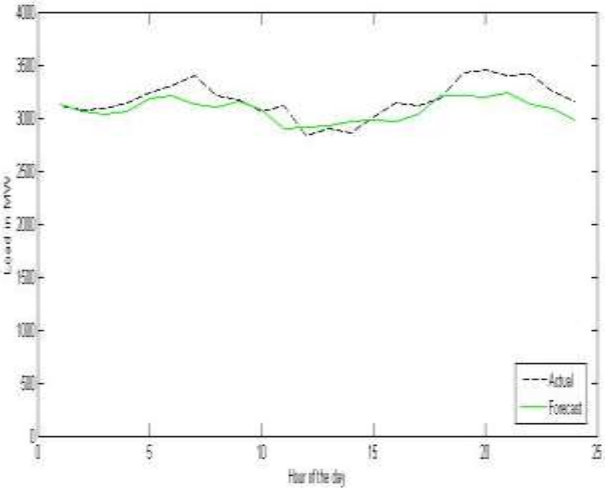

Figure 5: Friday Load Forecast

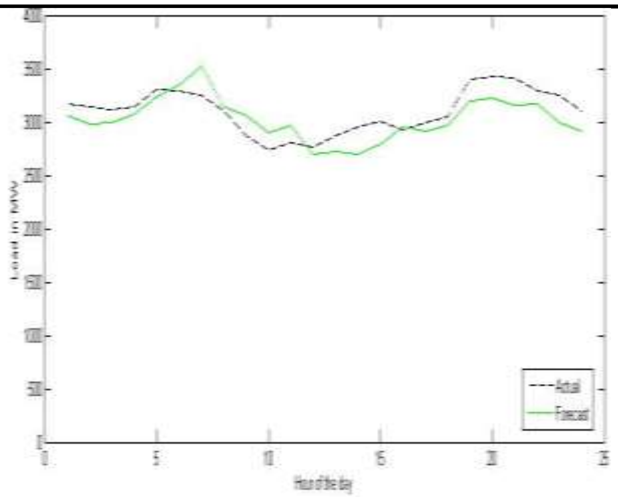

Figure 6: Saturday Load forecast

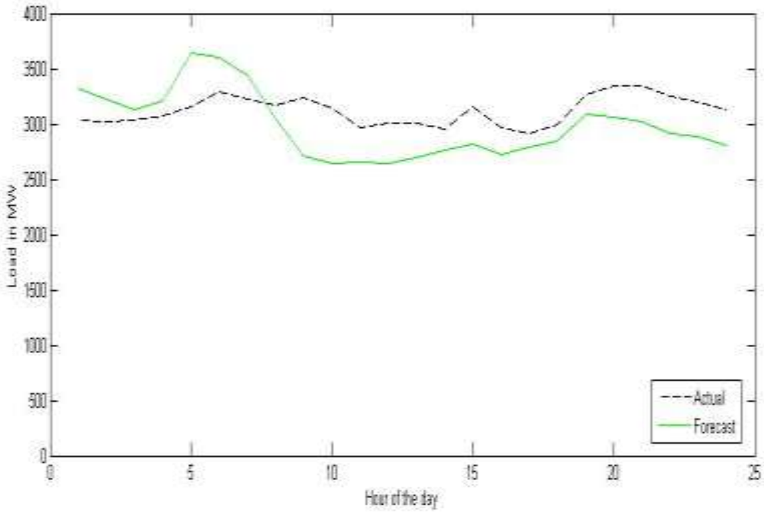

Figure 7: Sunday Load Forecast

CONCLUSION

It is clear from results obtained that ANN model could be used for accurate load predictions by utility companies especially when its operations are integrated with MATLAB platform. ANN forecasting model that utilizes previous load values, days of the week and hours of the day as demonstrated in this work could be implemented, tested, and improved. This model has been applied to Nigeria's electric power system load platform to forecast on short- term basis using realistic data provided by the country's National Control Centre with satisfactory results obtained when compared with the actual load on ground. Root mean square error of 0.51% was obtained for the short-term prediction scenario considered in this research. Thus, ANN proved to be a valid and promising technique for forecasting electricity consumption useful for better planning for equipment maintenance, repair, and expansion that would guarantee adequate power stability and distribution.

RECOMMENDATIONS

Since ANN model developed has shown capability to work on the Nigerian power system, it is recommended for adoption by National Control Centre (NCC), Osogbo - Nigeria for electrical load forecasting rather than the regressive or similar day method being utilized at present. This would ensure proper coordination of various generating stations spanned across the country for increased efficiency and effectiveness. ANN model could also be improved by strengthening its structure and improve its data set.

Also, incorporation of factors such as; economic factor, industrial operational trend, weather, and random events would further enhance the training data set leading to an improved ANN output.

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