Prediction of Weather-Related Electric Power Interruptions on the 33 kV Bonsa Feeder Using Artificial Neural Networks*

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Normanyo, E. and Dadzie, G. (2020), "Prediction of Weather-Related Electric Power Interruptions on the 33 kV Bonsa Feeder Using Artificial Neural Networks", *Ghana Journal of Technology*, Vol. 5, No. 1, pp. 29-39

Abstract

The objective of this study is to establish the relationship between weather parameters such as rainfall, temperature, wind speed and relative humidity and power interruption of a 33 kV feeder and to develop an Artificial Neural Network (ANN) model for the prediction of these weather-related power interruptions. Four years data spanning 2013 to 2016 on the weather parameters for the geographical area and number of recorded outages on the feeder were taken. These data were used to develop the prediction model. The data were used to train, validate and test the performance of the network and that of 2016 were used to predict the number of outages. The Levenberg Marquardt algorithm was used to train the network. Different models were developed to predict the occurrences of the outages based on a total of nine scenarios. This was also done to investigate which parameters had the most influence on the outage events. The weather data for 2016 were used as new inputs (sample) to the networks, and all the networks were simulated to predict the number of outages. The results showed that the ANN model was able to predict the number of outages with a reasonable level of accuracy. Rainfall and wind speed were established as the critical causes of the outage events while temperature and humidity had minimal influence on the outage events.

Keywords: Artificial Neural Network, Bayesian Regularisation, Levenberg Marquardt, Mean Squared Error

1 Introduction

The landscape of Tarkwa-Nsuaem municipality is generally undulating with ridges and valleys parallel to one another. The ridges rise over 70 m above the valley floors. The municipality falls within the rain forest belt with the height of trees ranging between 15 – 40 meters. It has a humid, tropical climate with an average annual rainfall of over 1680 mm. The rainfall is characterised with lightning and thunderstorms. The average annual temperature ranges between 26 ^{o}C in August and 30 ^{o}C in March. Sunshine duration for most of the year averages 7 hours per day (Anon., 2016; Nyarko, 2014).

The Tarkwa-Nsuaem municipality is supplied by nine main electrical feeders, six at 33 kV voltage level and three at 11 kV voltage level. The municipality has an average load demand of about 34 MVA (2017 estimate) which is supplied from the national grid at a voltage level of 161 kV. Three transformers rated 161/33 kV step down this voltage to a voltage level of 33 kV. The bus-bar is fed with 33 kV which is stepped down to 11 kV at the Bulk Supply Point (BSP) which is the Atoabo substation.

The Bonsa feeder distribution network is a 33 kV radial overhead distribution line supplying about 3338 customers (2017 estimate). The average load on the feeder is 1.6 MVA. Protection schemes are provided to protect the feeder against faults which may lead to power outages. At the substation, there is a circuit breaker fitted with an ABB Distribution Protection Unit (DPU), and an advanced microprocessor-based relay for protecting the main supply line against three-phase faults and line-to-line faults. Overhead ground wires are provided on the steel mini-tower poles to intercept direct lightning strokes. The 11 kV lines are protected with in-line fuses and an auto recloser.

The duration of interruption is determined by the utility's protective devices and the particular event that led to the fault. Occurrences of interruptions in power distribution networks are almost unavoidable. Reliability is a significant factor in operating and maintaining electric power distribution systems. Reliability of power systems is generally designated as a measure of the ability of the system to provide consumers with adequate supply (Uhunmwangho and Omoroguiwa, 2014).

The problems and the damages caused to the consumer due to the inadequate voltage conditions, dips and short and long-time interruptions determine substantial additional costs.

Providing reliable electrical service is the number one priority of electric power distribution companies. Unfortunately, electric power distribution networks are facing some operational problems, one of which is unscheduled power interruptions. A typical distribution network saddled with this problem is the 33 kV Bonsa feeder of Tarkwa. According to Maharajan (2012), an interruption occurs when the supply voltage or

*Manuscript received April 20, 2020
Revised version accepted September 01, 2020

load current decreases to less than 0.1 per unit for about 1 minute. Interruptions can be sustained or momentary. Momentary interruption is any interruption that lasts for less than 1 minute, hence sustained interruption is any interruption that lasts for more than 1 minute.

Prediction of the possible future occurrences of these weather-related power interruptions on the Bonsa feeder and dissemination of the information to power utility company should help in planning for unscheduled power interruptions. Related researches on Artificial Neural Network (ANN) applications convince that it is possible to define and build a model using Artificial Neural Networks (ANNs), which can use the weather parameters as inputs and predict the occurrences of interruptions with reasonable accuracy (Sarwat *et al*., 2016).

An ANN is an information processing paradigm that is inspired by the way biological nervous system processes information (Maind and Wankar, 2014). They are nonlinear models that have the potential of being used as useful forecasting tools in a large number of application areas (Kaur, 2016). The basic computational unit in a neural network is the neuron or perceptron which consists of inputs, weights (W), a summing point, a bias (b) and a nonlinear activation function (f). The neuron acts as a parallel processing unit that performs simple mathematical operations on its inputs and imitates the functions of biological neurons in its unique process of learning. The scalar inputs are transmitted through connections that multiply their strength by the scalar weights to form the product. All the scalar inputs are added together with the bias. The result is the argument of a transfer function which produces the output. The bias is a weight that has a constant input of 1.

An ANN is typically defined by the interconnection pattern between the different layers of neurons, learning process for updating the weights of the interconnections and the activation function that converts a neuron's weighted input to its output activation. The grouping of these neurons into layers, the connections between these layers, the summation and transfer functions comprise the functioning neural network. Most ANN applications require a network that contains at least three layers of neurons: input, hidden and output layers. The layer of input neurons receives the data, the output layer sends information directly to the outside world and the hidden layer receives the signals from all of the neurons in the input layer. After the hidden layer performs its functions, it passes its output to all of the neurons in the output layer, providing a feedforward path to the output (Maind and Wankar, 2014).

By way of training, the ANN is adjusted to perform a particular application. Once the network is trained with a variety of patterns of input and output combinations, ideally, it should be able to predict the correct output when an input pattern is given randomly. There are two approaches to training; supervised and unsupervised training. Supervised training involves a mechanism of providing the network with the desired output either by manually "grading" the network's performance or by providing the desired outputs with the inputs. Unsupervised training is where the network has to make sense of the inputs without an outside help (Dike *et al*., 2018; Maind and Wankar, 2014).

Several algorithms have been proposed for training an ANN. The neural network learning algorithms play an important role in building an efficient forecasting model. The algorithms are used to set the network’s weights in order to minimise the difference between the actual outputs and the target values produced by the network. Some of these algorithms are Levenberg-Marquardt (LM), Bayesian regularisation (BR) and Scaled Conjugate Gradient (SCG). The LM and BR use Jacobian calculations to perform their operations. LM is recommended for most problems, but for some noisy and small problems, BR can take longer computation time but obtain better solutions. For large problems, however, SCG is recommended as it uses gradient calculations which are more memory efficient than the Jacobian calculations the other two algorithms use (Anon., 2014; Kaur, 2016).

A number of weather-related variables are known to affect electric power outages and are duly reported in the literature. Notable among these variables are thunderstorms using regression tree models (Cerrai *et al*., 2019), probability distributions (Kabir *et al*., 2019), vegetation management combined with LiDAR-derived tree height data and random forest model (Wanik *et al*., 20017) and Bayesian prediction using historical high-resolution radar observations together with outage information (Yue *et al*., 2018); prediction of hurricanes making use of binary classification, multi-class classification, regression, random forest algorithm and with weighted mean absolute error (Shashaani *et al*., 2018), use of hurricane outage prediction model that included trees (D’Amico *et al*., 2019), utilisation of logistic regression (Eskandapour and Khodaei, 2017) and use of random forest model (Nateghi *et al*., 2014); Arif and Wang (2018) used statistical analysis and deep neural networks to predict repair and restoration times of distribution networks incapacitated as a result of outages caused by both thunderstorms and hurricanes. Outages caused by snow and ice storms were predicted by Cerrai *et al*. (2020) using machine learning-based model and a generalised linear model. Yan *et al*. (2016) predicted weather-caused blackouts by combining ArcGIS mapping with historical outage events and weather forecast data. Temperature (Bartos *et al*., 2016), rainfall and humidity (Sawart *et al*., 2016) and wind (Matavalam, 2004) also affected electric power outages. Clearly, thunderstorms and hurricanes were much researched however, no research, to the best of our knowledge, combined wind, rainfall, temperature and humidity for power outages prediction. For a town like Tarkwa, these four weather-related elements aside of lightning stroke, can be crucial in predicting outages experienced by a typical feeder. The objective of this paper is therefore, to utilise readily available historical data on wind, rainfall, temperature and humidity to predict outages experienced by numerous customers that are served with electric power from the Bonsa distribution feeder. More so, no such study was done with regard to the Bonsa feeder. Recommendations from this research stand to be useful to the utility company responsible for the feeder in question.

The rest of this paper is organised as follows: In Section 2, analysed outage data and meteorological data on the four weather elements are presented together with ANN models development and usage for the prediction. The results and discussion are presented in Section 3 with emphasis on performance of the models and the simulation results with their discussion. The conclusions and recommendations are given in Section 4.

2 Resources and Methods Used

2.1 Data Analysis and Integration

The two types of data, namely outage and meteorological data, were used to develop the models. The meteorological data were used as inputs to the network to establish a relationship between the weather parameters and outage event. The outage data were used as a target to teach and direct the network to produce the desired results. The prediction was based on monthly data since the number of outages experienced per day was insufficient to produce a good prediction model. Fig. 1 and Fig. 2 show the analysed outage and meteorological data, respectively.

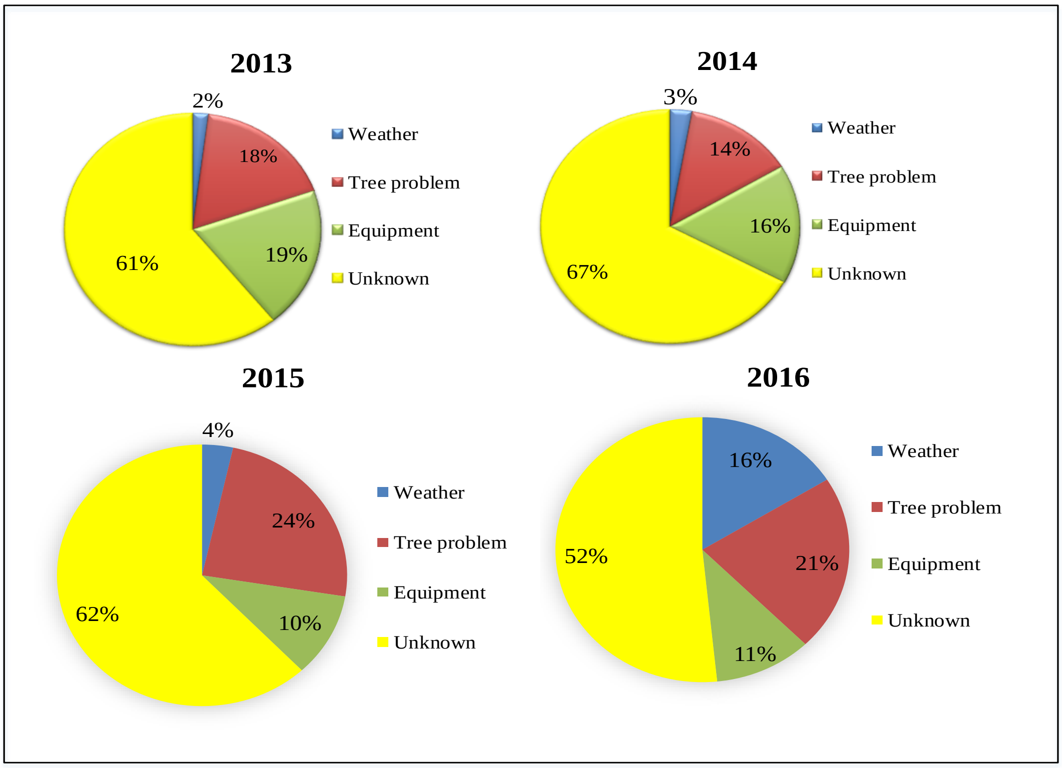

Fig. 1 Analysed Outage Data for the Study Period

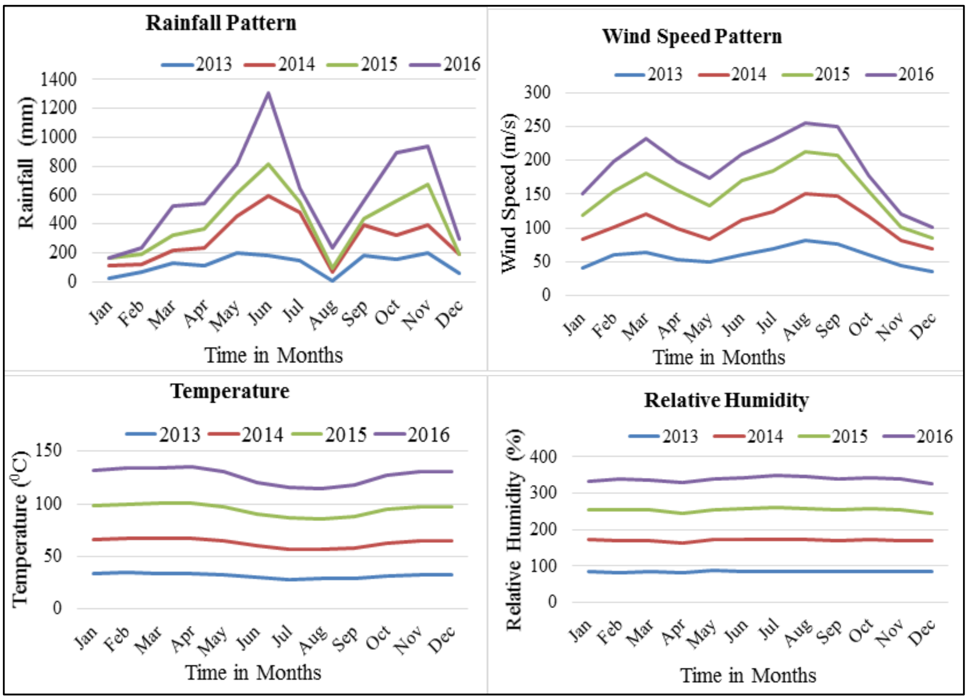

Fig. 2 Analysed Meteorological Data for the Study Period

2.2 Development of the Artificial Neural Network Model

The prediction models were developed based on each of the weather parameters and a combination of them. The weather and outage data from 2013 to 2015 were used to create the network, train and validate the performance of the network and that of 2016 were used for the prediction. The training parameters were changed depending on the network's performance until an excellent performance was achieved. A flowchart of the proposed weather-related interruption prediction method is presented in Fig. 3.

The steps involved in the development of the weather-based interruption prediction model illustrated in Fig. 3 are as follows:

Step 1: Start to initialise MATLAB software.
Step 2: Load weather and outage data into MATLAB software and select the NN toolbox.
Step 3: Define inputs and target in the NN toolbox, prepare data for training, validation and testing, select the network's architecture and select the training function.
Step 4: Train, validate and test the network.
Step 5: Is the performance of the network good? If yes, proceed to the next step but if no, change the number of neurons and then go back to step 4.

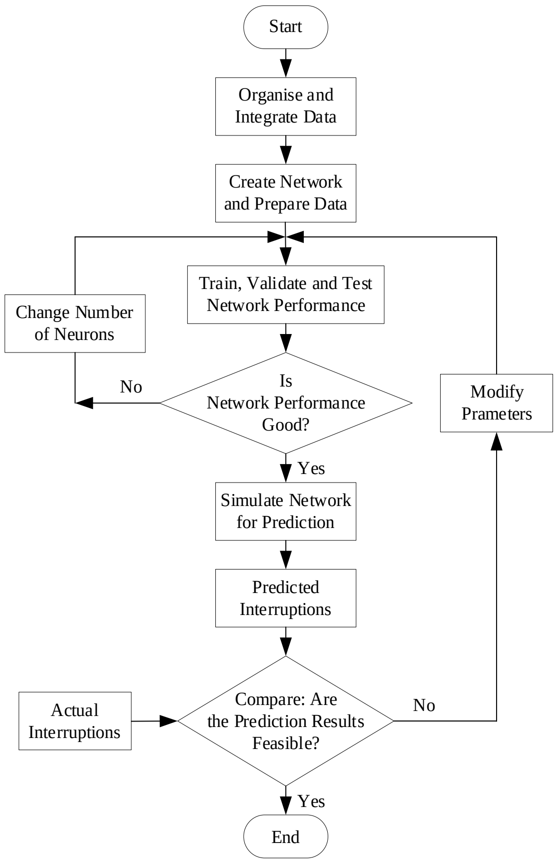

Fig. 3 Flowchart of the Weather-based Interruption Prediction Model

Step 6: Simulate the network for prediction. The output of the simulated network is the predicted number of outages and the actual number of outages which were used as the target.
Step 7: Compare the actual and predicted interruptions. Is the predicted result feasible? If no, modify the training parameters and go back to step 4, if yes end.
Step 8: End.

The time series app. in the neural network toolbox was used to develop the ANN models. This tool allows the user to solve three kinds of problems, namely Nonlinear Autoregressive with External Input (NARX), Nonlinear Autoregressive (NAR) and Nonlinear Input-Output (NIO). NARX allows the user to predict series y(t) (targets) given past values of y(t) and another series x(t) (inputs), NAR predicts series y(t) given past values of y(t) and NIO predicts series y(t) given past values of series x(t). NARX was selected to develop the model and for the prediction. This was because the prediction of the number of outages was based on past occurrences of these outages and weather data which were considered as external inputs. According to Anon. (2014), NARX solutions are very accurate for this type of prediction than the others.

Different models were developed to predict the occurrences of these outages (using the available data from 2013 to 2015) based on a number of scenarios. The scenarios are as follows:

(i) The individual weather parameters were used as input to the network;
(ii) Rainfall and wind speed were used together as inputs to the network;
(iii) Temperature and humidity were used as the inputs;
(iv) Rainfall, wind speed and temperature were used as inputs;
(v) Rainfall, wind speed and humidity were used as inputs; and
(vi) All the weather parameters were used together as inputs to the network.

In all these scenarios, the network design was changed to enhance performance. The optimal number of hidden neurons for each network was obtained experimentally by changing the network's design and running the training process several times until an excellent performance was achieved.

2.2.1 Creation of the Artificial Neural Network

The weather parameter data points from the year 2013 to 2015 (total of 36) were imported into the toolbox as inputs and the number of outages as the targets.

After defining the inputs and targets, the next step was to randomly divide the dataset into training, validation and testing datasets. Training always requires a larger dataset than validation and testing. The division was done using percentages, and this depended on the size of the available data. By default, 70% of the data was used for training, and the remaining 30% was used for validation and testing. (Anon., 2014; Sawart *et al*., 2016). The ANNs were then created using the available data. This was simply done by defining the type of network architecture, the number of layers and the number of neurons in each layer. According to Nazir (2015), three layers are enough to solve any problem though depends on the nature of the problem. The number of hidden layers and nodes also depend on the number of input parameters and the type of network architecture selected. The number of neurons in the input and output layers depend on the number of inputs and outputs. For this study, a three-layer feedforward network (input, hidden and output layers) was selected for the models. The number of hidden neurons were selected based on the inputs to the networks and the performance of the networks. A graphical diagram of the model developed for the prediction is presented in Fig. 4.

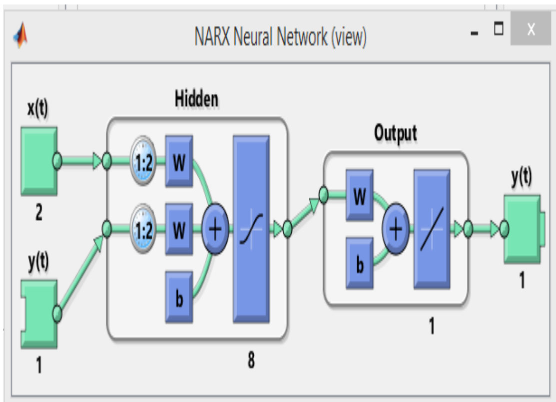

Fig. 4 Graphical Diagram of Artificial Neural Network Model

2.2.2 Training, Validation and Testing

The Levenberg-Marquardt (LM) algorithm was employed in the training of the ANNs. This algorithm is recommended for most problems because it is the fastest method for training moderate-sized feedforward neural networks.

The ANNs were trained for a fixed number of epochs (iterations) several times until an excellent performance was achieved. A snapshot of the neural network training process is shown in Fig. 5.

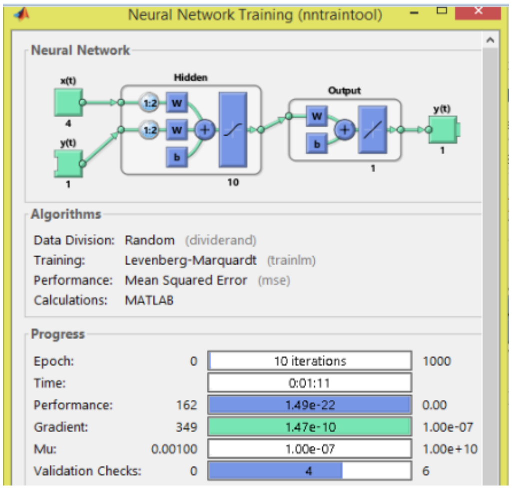

Fig. 5 Training Process of the Artificial Neural Network Model

3 Results and Discussion

3.1 Performance of the Artificial Neural Networks

The performance of the network was evaluated by the Mean Squared Error (MSE) and the Regression (R). MSE is the average squared difference between outputs and targets. Lower values are better. Zero means no error. The R values measure the correlation between outputs and targets. An R value of 1 means a close relationship and 0 means a random relationship. The performance of all the network models is presented in Table 1. The level of accuracy of the predicted result is dependent on the performance of the network during training, testing and validation. Excellent performance leads to a high level of accuracy. For this study, all the MSE values are above 1, and this is acceptable due to the method employed and the data used in the prediction of the outages. The total number of outages were used as targets, but the output of the network was the number of outages due to weather. There were times where the output was less than the target and times where the output was more than the target and this resulted in the higher MSE values. MSE varied according to the type of input and its effect on the outages. All the R values were above 0.5 and this indicates that there is a good relationship between the output and targets. A good relationship means that the network has a high level of accuracy, and hence the predicted results are also very accurate. From the Table 1, the network with rainfall and wind speed as the inputs is the best model since it has the best performance in terms of R and MSE.

3.2 Simulation Results

The output of the ANN is two columns of data; a prediction for each entry in the evaluation dataset and the actual number of interruptions for each entry in the evaluation dataset. Graphs representing the actual and predicted outages are presented in Fig. 6 to Fig. 14.

Table 1 Performance of the Artificial Neural Network Models

Network Input	**MSE**	**Regression (R)**			
		Training	**Validation**	**Testing**	**All Dataset**
Rainfall	7.750	0.919	0.885	0.700	0.817
Wind Speed	7.165	0.891	0.500	0.505	0.698
Temperature	1.631	0.902	0.992	0.724	0.804
Relative Humidity	8.754	0.837	0.604	0.743	0.737
All Four Parameters	10.218	0.976	0.704	0.780	0.816
Rainfall, Wind Speed and Relative Humidity	8.224	0.738	0.612	0.753	0.710
Rainfall, Wind Speed and Temperature	6.894	0.937	0.871	0.514	0.848
Temperature and Relative Humidity	12.165	0.775	0.542	0.551	0.603
Rainfall and Wind Speed	1.605	0.956	0.990	0.884	0.911

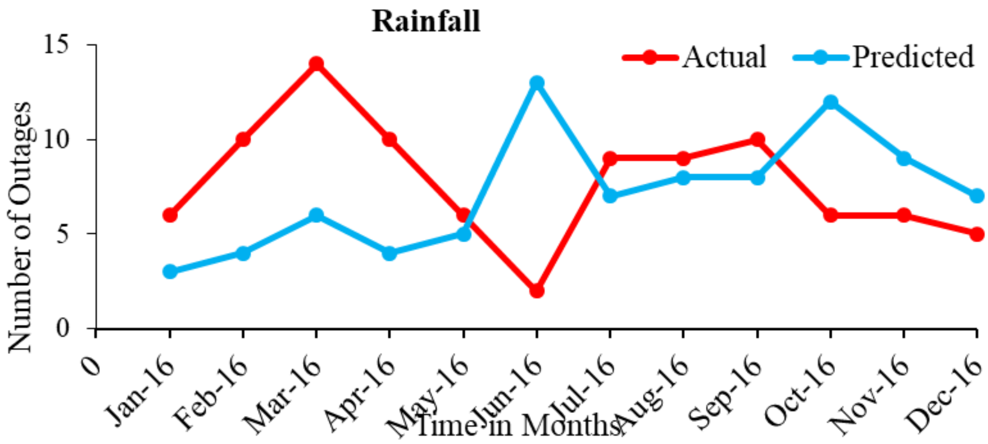

Fig. 6 Prediction Pattern of Number of Outages of the Model with Rainfall as Input

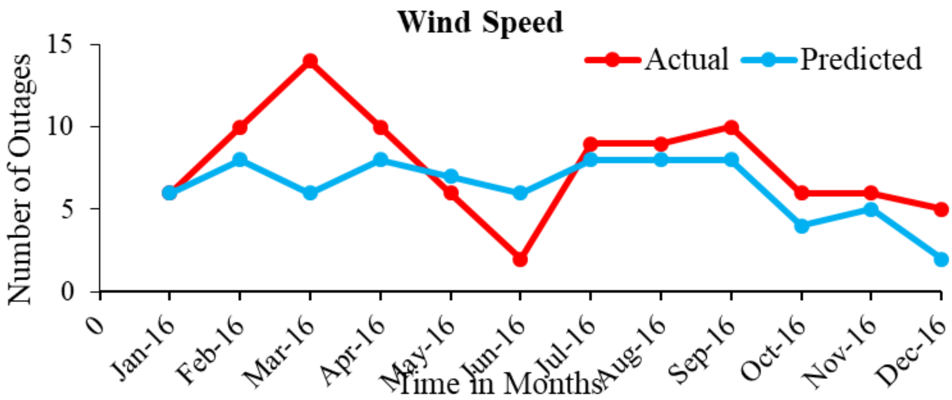

Fig. 7 Prediction Pattern of Number of Outages of the Model with Wind Speed as Input

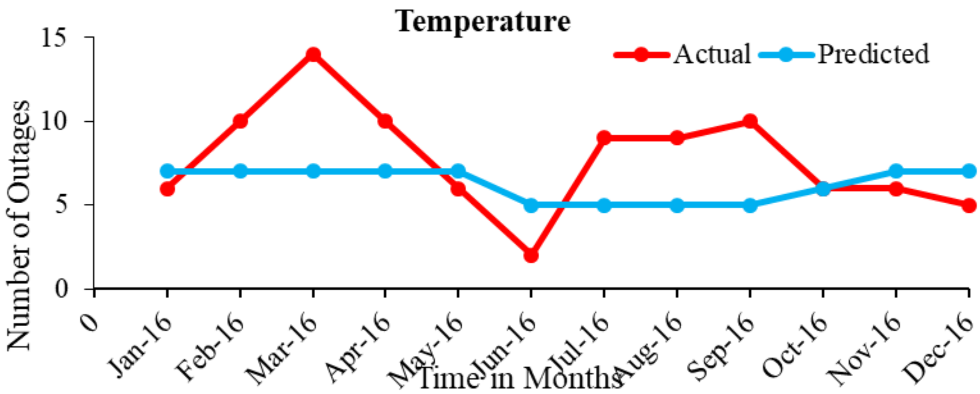

Fig. 8 Prediction Pattern of Number of Outages of the Model with Temperature as Input

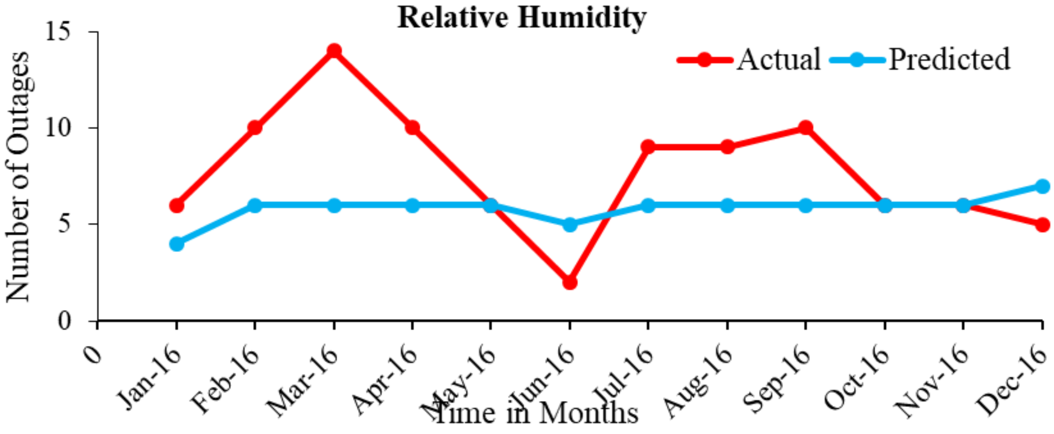

Fig. 9 Prediction Pattern of Number of Outages of the Model with Relative Humidity as Input

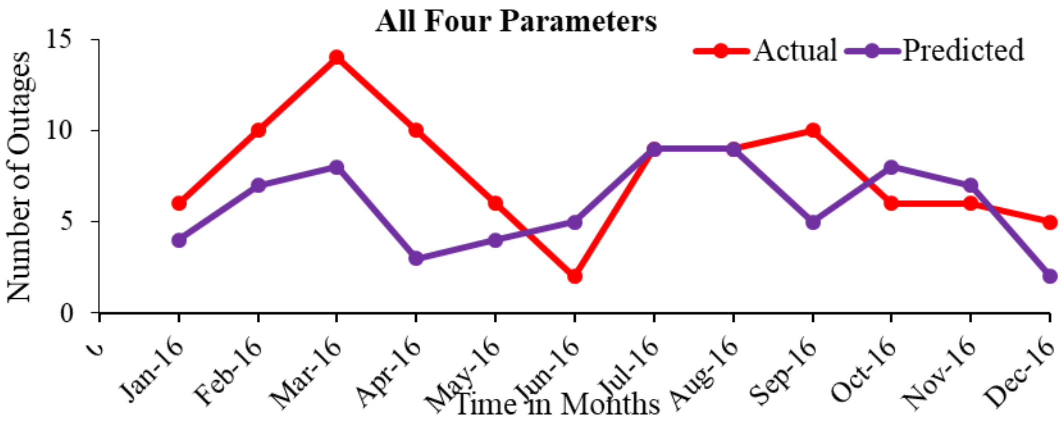

Fig. 10 Prediction Pattern of Number of Outages of the Model with Rainfall, Wind Speed, Temperature and Relative Humidity as Inputs

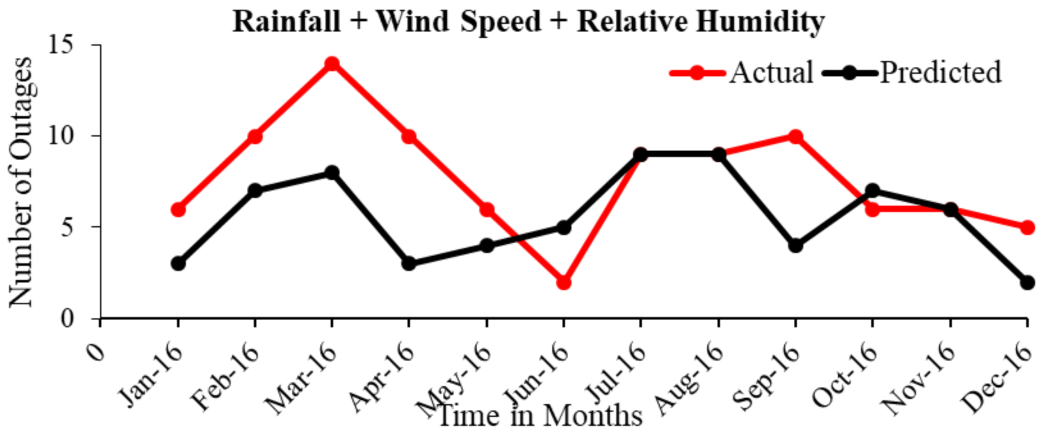

Fig. 11 Prediction Pattern of Number of Outages of the Model with Rainfall, Wind Speed and Relative Humidity as Inputs

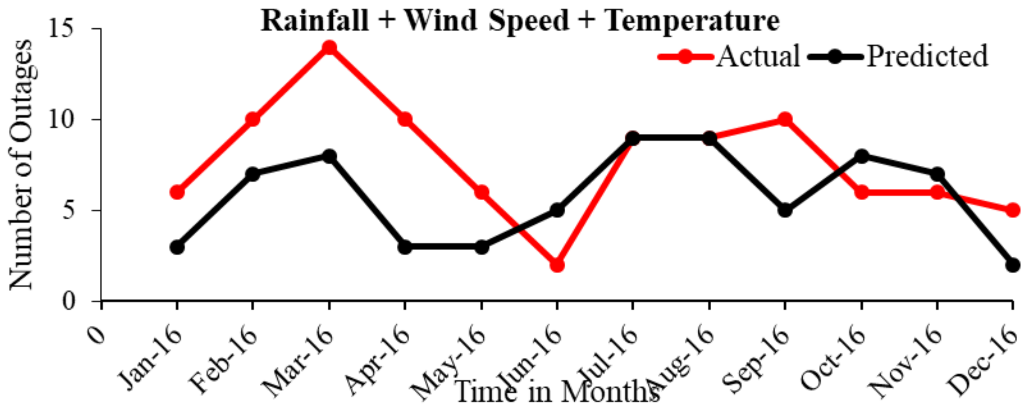

Fig. 12 Prediction Pattern of Number of Outages of the Model with Rainfall, Wind Speed and Temperature as Inputs

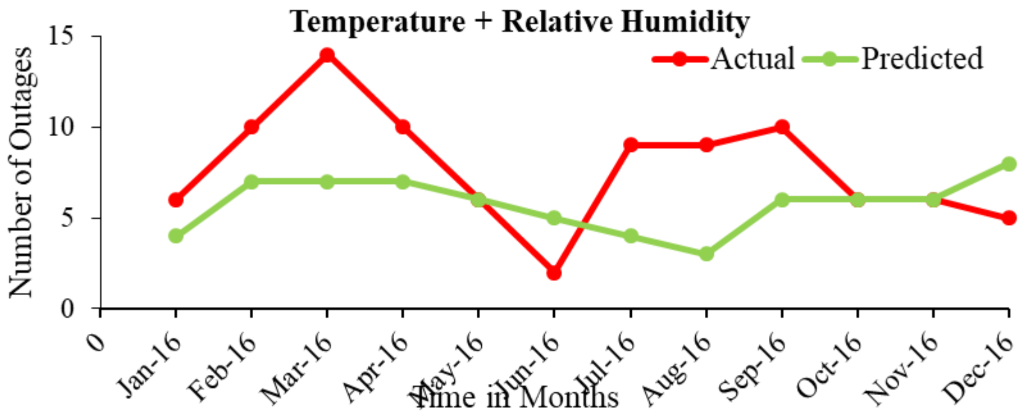

Fig. 13 Prediction Pattern of Number of Outages of the Model with Temperature and Relative Humidity as Inputs

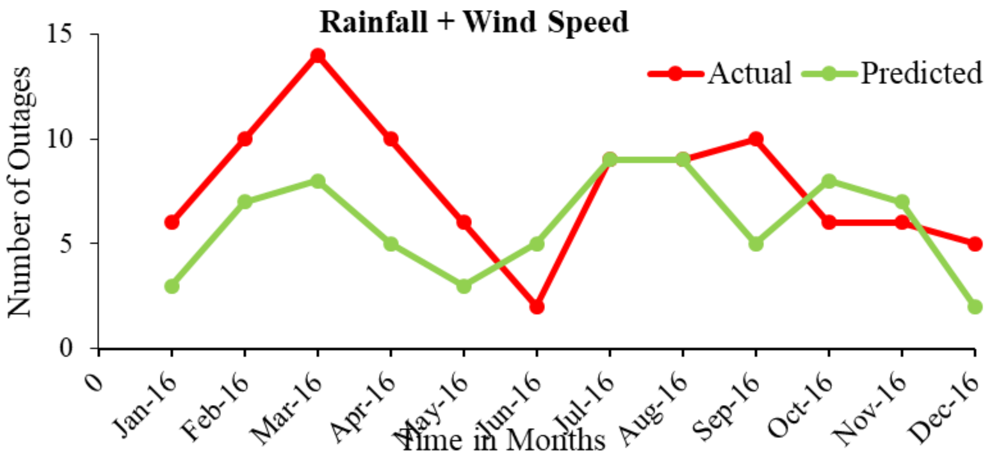

Fig. 14 Prediction Pattern of Number of Outages of the Model with Rainfall and Wind Speed as Inputs

3.3 Discussion of Simulation Results

The simulation results show that in the cases of rainfall (Fig. 6) and wind speed (Fig. 7), the changes in weather conditions as evidenced in Fig. 2 forced the ANN model to predict the number of outages as proportional to the changes. On the other hand, the predicted number of outages were almost constant in the case of temperature (Fig. 8) and humidity (Fig. 9) meaning rainfall and wind speed had a greater influence on the outage events but temperature and humidity as individual weather parameters had little or no influence on the outage events. The changes in the actual values of temperature and humidity for the period of study as presented in Fig. 2 were too small to influence the model.

Comparing the predicted values of Fig. 10, Fig, 11 and Fig. 12, it can be seen that only rainfall and wind speed of the four weather parameters account for most of the variation in the number of interruptions hence, the temperature and humidity effects can be neglected. This observation can be confirmed from Fig. 13 and Fig. 14 as well where the predicted outages were not similar. Fig. 13 differed from Figs. 10, 11 and 12 whilst Fig. 14 proved otherwise. Therefore, the prediction model selected for the study was the model in Fig. 14 with rainfall and wind speed as inputs. Detailed observation of the results in Fig. 14 shows that there were cases where the predicted outages were less than the actual, more than the actual and equal to the actual.

3.3.1 Predicted Outages Less than Actual

Where the predicted outage values were less than the actual, the number of the predicted outages matched the number of weather-related outages that occured.

3.3.2 Predicted Outages More than Actual

The weather conditions for these months were relatively high. This large change in weather conditions forced the ANN model to predict the number of outages proportional to the weather conditions. The actual number of outages for these months were pretty small though their weather conditions vary over a wide range. The reason was that precautionary measures such as tree trimming, maintenance of equipment such as insulators, cross arms and lightning arrestors were very effective during these months. They reduced the influence of high rains and wind speed on the occurrences of these outages.

3.3.3 Predicted Outages Same as Actual

These months were close to the beginning of a minor rainfall season where the influence of wind is high and so therefore the model was forced to predict the number of outages proportional to the high wind speeds experienced during the period.

4 Conclusions and Recommendations

It has been shown from this research that ANN has the potential to provide powerful modelling tools, and can be used to provide limited real-time prediction. The accuracy and precision of the model is dependent as much on the input of the ANN model. Whenever the number of interruptions is forecasted based on historical weather data, the utilities can prevent a major percent of these events by establishing preventive maintenance programs.

It is therefore recommended that:

(i) There should be proper vegetation management to reduce the faults caused by vegetation growth.
(ii) The performance of the whole distribution network (including all the nine feeders) should be investigated and used for the prediction of the weather related-outages, in that case, the prediction model will be based on the daily number of outages which will provide better results.
(iii) Other types of ANNs or their combinations should be tested to see which of the models gives better prediction results.
(iv) The use of ANNs for fault diagnosis, transient stability assessment and static and dynamic security assessment should also be considered to reduce the number of faults with an unknown cause.

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