



SINGLE TOPOLOGY NEURAL NETWORK-BASED VOLTAGE COLLAPSE PREDICTION OF DEVELOPING POWER SYSTEMS

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Abstract

Most modern power systems operate within the vicinity of saddle-node bifurcation points because the network operators are hard put to estimating the margin to voltage collapse before the blackout. As a result, voltage stability analysis and control are growing concerns amongst electric power utilities. The selection of the hidden layer units and the training function algorithms for back propagation artificial neural network training are major challenges. Hitherto, comparative analyses of the training functions were made. Thereafter, the complexity of the artificial neural network topology was made very simple by selecting the hidden layer neurons via scripts written in Matlab software environment. To obtain the hidden layer unit, a script has to be developed in MATLAB to select a hidden layer neuron from a range of 10 to 65. The result shows that the optimal 55 hidden units have root mean square error (RMSE) of 0.05. The result was validated when the range of hidden layer neurons was extended to 100. The proposed approach was tested in a typical developing power system: a 45-bus Nigerian 330kV transmission network and proved to be fast and accurate for voltage collapse prediction.

1.0 INTRODUCTION

Majority of the modern power systems operate close to their knee points owing to some transmission constraints. These factors include but not limited to: outages of transmission lines or generators, incessant energy demand, insufficient/lack of reactive reserves, progressive voltage decline, total connected load exceeding the power supply, growth in load without an equivalent rise in transmission capacity [1-4]. These factors are peculiar to developing power systems which are faced with uphill tasks of maintenance, sustainability of quality, and secured power supply [5].

In 2017, 15 incidences of voltage collapse which occurred within the first quarter of the year cost Nigeria 100 billion United States dollars [1]. In addition, manufacturing industries and business owners have lost an average of 3.5 trillion naira per year to national black out. Those who are using fuel at home spent over 1.56 trillion naira, which is almost equal to 13.35 million dollars in that period. Moreover, documentation from the National Control Centre, Oshogbo shows that in 2013, Nigeria lost 1.3 billion naira to voltage collapse [1]. Again, according to the World Bank's report [6] on power sector

recovery operation in Nigeria in the year 2020, the yearly economic losses occasioned by voltage instability were pegged at 10.1 trillion naira. The amount of money spent is tantamount to Nigeria's gross domestic product. According to [7], Nigeria lost 29 billion United States dollars which is tantamount to 5.8 percentage of her yearly gross domestic product (GDP) in the year 2024 to voltage collapse. To proffer a short term measure solution, the report banks on the procurement and installation of supervisory control and data acquisition system to monitor and control the incessant outages.

1.1 Recent Trends or Challenges in Developing Power Systems

At present, the investigation of the menace of voltage collapse is a serious concern for researchers [8-9]. Owing to the unbundling of the power industry, the increase in the high cost of living, and the global economic meltdown, attention has drifted from shoring up the network's capacity to managing network facilities [10-11]. Mbuswe and Ekwue, [12] observed that insufficient reactive power resources, generators reaching their voltage control limit, technical and nontechnical losses are part of the factors that contribute to the unresolved rhetoric beleaguering the Nigerian power system. Some power systems experience voltage collapse every now and then because the loads rise to a certain threshold point, where the system cannot hold the amount of connected load practically [10]. To proffer solutions using artificial neural network, some researchers like [13], [14] and [15] created different topologies of back propagation artificial neural networks to evaluate the hidden units that will give the best performance for neural network application. However, such an approach is laborious, computationally intensive, and time-consuming. This work looks at other approaches exploited by some researchers and proposes a single topology Bayesian-back-propagation neural network for voltage collapse prediction, particularly for developing power systems.

In the work done in [16], the authors compared prediction by voltage collapse proximity indicator with artificial neural network in a practical Kenyan power network but no attention was paid to the selection of the hidden layer neurons and the training function in the simulation. In the work carried out by [17], it is believed that gradient descent algorithm converges faster than other training algorithms like Bayesian regularisation and Levenberg - Marquart algorithm but the accuracy is questionable. In [18], eight training function algorithms for the prediction of the line index of a transmission network

were made. The study proposed trainlm as the best performance function with low mean square error but not much effort was made on the Bayesian regularized algorithm which is of better accuracy than most of the training function algorithms.

In [19], five topologies of back-propagation artificial neural network were developed to obtain the hidden neurons that will produce the ultimate generalization of the ANN, but the approach is capital intensive. In the same vein, [20] exploited several trials to obtain the hidden neurons for good performance of the ANN, but the approach is drudging and stressful. It can be seen in [21] that the hidden layer neurons were arbitrarily chosen for voltage collapse prediction. The work compared continuation power flow and artificial neural network in terms of computational time. Although the result shows that ANN is better than continuation power flow (CPF) but it would perform better if the appropriate hidden layer neurons is optimally selected.

In [22], a Levenberg Marquart training function was arbitrarily selected, the hidden layer neuron of the back-propagation artificial neural network for voltage collapse prediction using fast voltage stability indicators was exploited. The results obtained were compared with Newton Raphson's load flow analysis. It was found that the implicit assumption made in the determination of the hidden layer neurons did not produce the same result when another value for the hidden layer neurons was chosen. Recently[23], there is a comparison between the performance of the prediction models of the artificial neural network and autoregressive integrated moving average model (ARIMA) model using root mean square error and mean absolute percentage error as performance criteria. From the results [23], the study validated the capability of ANN for maximum temperature and solar radiation prediction but little attention was paid to the optimal choice of the hidden layer neurons and the choice of the training function for the accuracy and time of the predictions. In [24], five feed forward artificial neural network techniques for voltage collapse predictions were compared but no attention was given to the selection of hidden layer neurons.

In [25], previous investigations were improved upon by arbitrarily creating a single topology-based ANN. Although the results obtained indicated a high correlation coefficient whose value is 0.9975, with a small mean square error (MSE) of 0.000021824, there is no guarantee that further simulations could produce the same performance. Atiqa et al [26], made an exploit of multilayer perceptron artificial neural



network for voltage collapse prediction. In the work, the hidden units of the neurons were arbitrarily chosen as five without considering what the result of the model becomes when the range is extended for the neurons of the higher values.

The contribution of this paper to knowledge includes but not limited to the following points:

- i. The development of a technique to determine the optimal number of hidden layer neurons to be used for the ANN simulation.
- ii. The challenges of over-fitting and under-fitting of data owing to random selection of hidden layer neurons are solved.
- iii. The application of the technique on the Nigerian power system network.
- iv. The comparative analysis of the training function techniques for the voltage collapse prediction.
- v. The application of VCPI on Nigerian power system network.

2.0 METHODOLOGY

2.1 Algorithmic Developments

The following steps were used in a typical example of a developing power network, precisely the 45-bus 330kV Nigerian transmission system. The steady-state analysis of the Nigerian 330kV transmission system was carried out to obtain the real power flow along the transmission lines as well as the voltages on the buses. The following steps of the algorithm development were introduced.

- i. The voltage collapse proximity indicator (VCPI) is a measure used to ascertain the proximity to voltage collapse, [27]. The VCPI was calculated based on Equation 6.
- ii. The results obtained in Step i are compared with those obtained from Bayesian back propagation artificial neural network (BPANN) simulations.
- iii. The flow of true power along the transmission line and the maximum power the transmission line can transfer are the inputs to BBPANN.
- iv. The transfer function in the hidden layer which comprises the optimum 55 neurons is the tan sigmoid transfer function. There is one pure linear transfer function at the output layer. The target output is the voltage collapse proximity indicator. The choice of topology for BPANN training is one of the major challenges for its experts. The task has always been to optimize the complexity of the model to achieve the best generalization. Experts vary the complexity of the topology by changing the number of neurons in the hidden layer of the network by a push-barrow approach. However, a choice of few hidden units gives in to under-

fitting, and that of over selection of hidden units caves in to over-fitting.

- v. To determine the number of neurons in the hidden layer, a MATLAB script was developed to determine the optimal number of neurons that produces the best generalization by varying the hidden layer neurons from 10 to 100 and from 10 to 60 neurons in steps of 5.
- vi. Train with gradient descent algorithm
- vii. If the error is tolerable for voltage collapse prediction go to the next step, otherwise, revert the weight to step vi
- viii. Train with other patterns
- ix. If the error is tolerable for voltage collapse prediction, go ahead and carry out the prediction, otherwise, re-initialize the weight.
- x. Stop

The output of a neuron which is can be taken as $G_{m,3}$ is juxtaposed with the target value T_m to estimate the error $\hat{\epsilon}_m$ as

$$\hat{\epsilon}_m = T_m - Q_m \tag{1}$$

Where, $Q_m = G_{m,3}$. The square of the error forms the objective function as

$$\hat{\epsilon}_m^2 = (T_m - G_{m,3})^2 \tag{2}$$

Summing up the square of the error ($\hat{\epsilon}_m^2$) forms the objective function as thus:

$$\hat{\epsilon}_m^2 = \sum_{m=1}^q \xi m^2 = \sum_{m=1}^q [T_m - G_{m,3}]^2 \tag{3}$$

The original weight is given as W_0 , the weight update is given by

$$W_{kl,2}(k + 1) = W_{kl,2}(k) + \Delta W_{kl,2} \tag{4a}$$

$$\text{Where, } \Delta W_{kl,2} = -\beta \frac{\partial \hat{\xi}^2}{\partial W_{kl,2}} \tag{4b}$$

The local and global minimum points are shown in Figure 1. Where, β = learning rate and $\frac{\partial \hat{\xi}^2}{\partial W_{kl,2}}$ is the first derivative of the square error with respect to the weight.

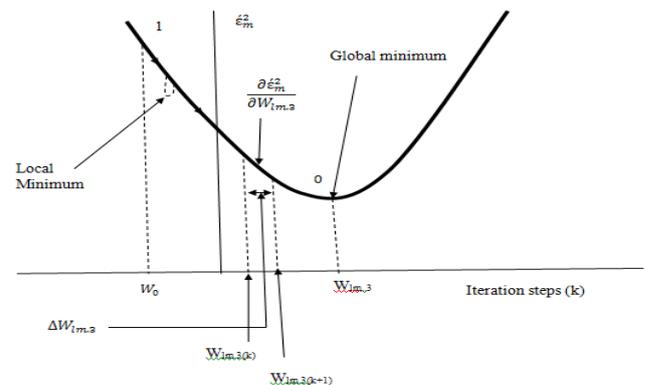


Figure 1: Minimization of square error

However, the gradient descent algorithms used did not attain global minimum point but got stuck at the local



minimum owing to its avoidance of momentum constant as shown in Figure 1. To jump across the ditch, an exploit of Levenberg Marquart Algorithms and Bayesian regularized neural network were made. While the former was designed to approach second-order training speed without having to compute the Hessian matrix, the latter uses the Jacobian for calculations, which assumes that performance is a mean or sum of squared errors. The Jacobian matrix contains the first derivatives of the network errors for the weights and biases. The Jacobian matrix can be calculated through a standard back propagation technique which is much less complex than computing the Hessian matrix.

3.0 RESULTS AND ANALYSIS

3.1 Data Pre-Processing

For the data normalization, the input data and the output data were taken into consideration. Because of the nature of the input and the hidden units, the nonlinear activation function like the tan sigmoid activation function was considered. For the target, a linear activation function (purelin) was used for the simulation. The relevance of data normalization is to ensure network optimization and a higher probability of obtaining an excellent result.

3.2 Performance Criteria

To analyze and evaluate the prediction performance of ANN, the RMSE, MSE, and regression (R) were used as performance indicators.

The RMSE is given by [28]:

$$RMSE = \frac{1}{M} \sqrt{\sum_{i=1}^M (v_i - \hat{v}_i)^2} \tag{5}$$

Where, v_i is the real value of the output, \hat{v}_i is the value of the output to be predicted, and M is the sample to be subjected to test.

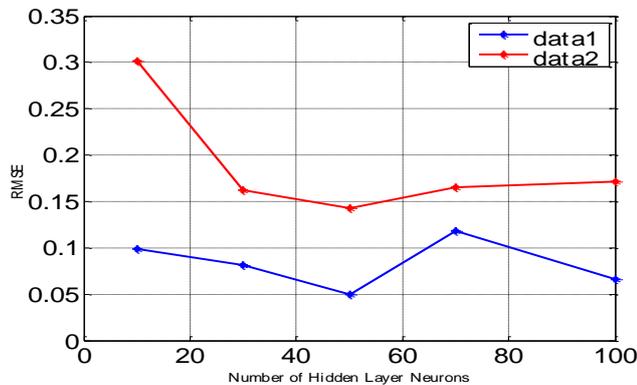


Figure 2: First trial for selecting the hidden layer neurons

To obtain the hidden layer neurons, a script was developed in MATLAB to evaluate the optimal

hidden neurons that produce the best generalization. Simulations using the first range of neurons (10 to 100) obtained a Root Mean Square Error of 0.05 at 55 hidden layer neurons as shown in Figure 2. To reduce the number of iterations and minimize the simulation time, the result was validated when the script was tested with the second range of neurons (10 to 65). The result obtained has the same RMSE and optimal hidden layer neurons of 55 as shown in Figure 3. Training in the network automatically stopped when generalization stopped improving, as indicated by the decrease in the RMSE of 0.05.

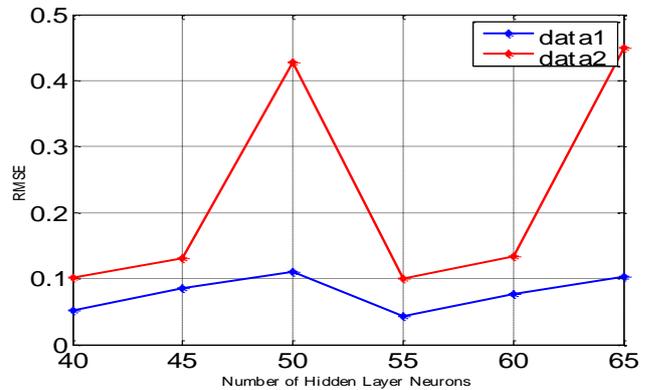


Figure 3: Second trial for selecting the hidden layer neurons

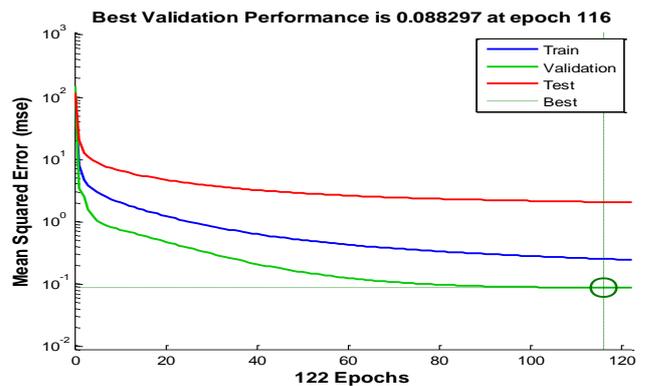


Figure 4: Performance characteristics curve for gradient descent

3.3 Mean Square Errors and Regressions as Performance Criteria for Selecting the Training Function

First, training with the gradient descent algorithm produced the best validation performance of 0.88297 at 116 epochs and 10 seconds as espoused in Figure 4 and Table 1. Albeit, training, validation, and testing follow the same trend, the iteration processes seem to have got stuck at the local minima owing to the avoidance of a unit momentum constant. Ignoring momentum made the network get stuck in a shallow local minimum. The presence of momentum could have made the network slide through a shallow local

minimum. There is no perfect correlation coefficient in training with gradient descent as can be observed in Table 1.

Second, in training with Levenberg Marquart (LM), it took the algorithm 1 second to have the best validation performance of 0.083152 at the 4th epoch. The regression is 0.996321, which is approximately equal to 1. The validation performance of gradient descent, Levenberg Marquart, and Bayesian regularisation (BR) are respectively shown in Figures 4, 5 and 6. Training with BR has a correlation coefficient of 1 as can be observed in Figure 7. This shows that there is a close mismatch between the input variables and that of the output. From the results of the three training algorithms, the Bayesian regularized technique has the best performance in terms of reduced mean square error. Table 1 show that the percentage error between LM and BR is 89%. By far, BR is better than LM regarding reduced MSE performance criterion. The lower the MSE, the better the training and the more accurate the prediction results. As a result, a Bayesian Regularised Artificial Neural Network (BPANN) is proposed for a single topology-based neural net voltage collapse prediction.

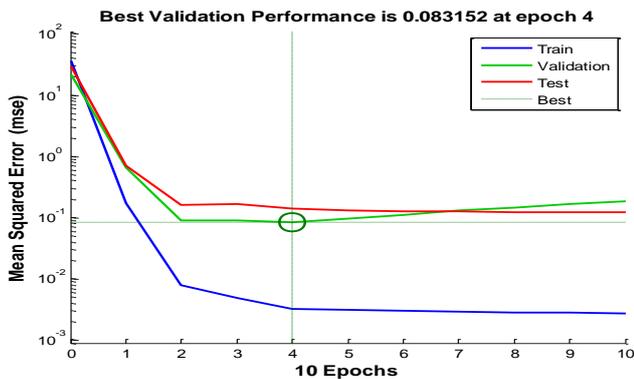


Figure 5: Performance characteristics curve for Levenberg Marquart algorithm



Figure 6: Performance characteristics curve for Bayesian regularization algorithm

Table 1: Between heuristic and numerical algorithms for the training algorithms

S/N	Training function	Mean Square Errors(MSE)	Regressions (R)	Epochs	Time (s)
1	TrainGD	0.088298	0.74693	116	10.0
2	TrainLM	0.083152	0.99631	4	1.0
3	TrainBR	0.0091068	1.0000	66	4.0

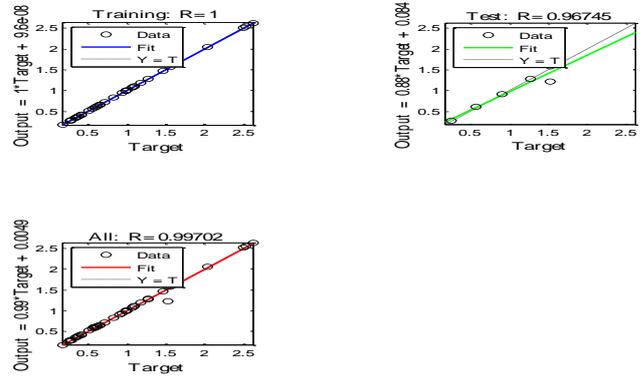


Figure 7: Regression Plot for the Bayesian Regularization Algorithm

3.4 Voltage Collapse Prediction Using VCPI and ANN

There is a need to compare the conventional VCPI and the numerical algorithm to ascertain which is superior for voltage collapse prediction. The voltage collapse proximity indicator as applied in [] is calculated using Equation 6.

$$VCPI = \frac{P_a}{P_{max}} \tag{6}$$

Where, P_a is given as the true power that can be transferred along the transmission line. P_{max} is given as the highest true power the transmission line can evacuate. However, the highest true power obtainable at the receiving end at any instant is given as;

$$P_{a(max)} = \frac{V_a^2 \cos \phi}{Z} \left(\frac{\theta - \phi}{2} \right) \tag{7}$$

However, Z is taken as the load impedance, the sending end voltage is taken as V_a , and the angular phase difference is ϕ . It is given as $\tan^{-1}(Q_a/Q_a)$, θ is the phase angle obtained from Newton Raphson’s load flow analysis. A VCPI value less than 1 show that the line is stable, and a value equal to or above 1 shows voltage instability. This approach has the merit of showing the capability of closeness of a network to voltage collapse as well as bringing to bare the mechanisms that cause voltage collapse.

The total transmission lines of the 45-bus, 330kV Nigerian transmission systems are 53. To ascertain the prediction using BR, the real power flow along the transmission line and the maximum real power that the line can evacuate are the two input vectors to the BPANN. Figure 8 shows a close relationship between

the results obtained for voltage collapse prediction using VCPI and BBPANN, but the latter is more accurate than the former from the given results. The prediction for 80% of the input data presented to the network for training is shown in Figure 5. The network was trained and adjusted according to the Bayesian regularized network owing to its accuracy. In Figure 9, the prediction for 20 percent of the input data used for network generalization is shown. The training was halted when generalization stopped improving. In Figure 9, the difference between the actual values and the predicted values are too small to be considered. The slight variation in the predictions shows that BPANN is more accurate.

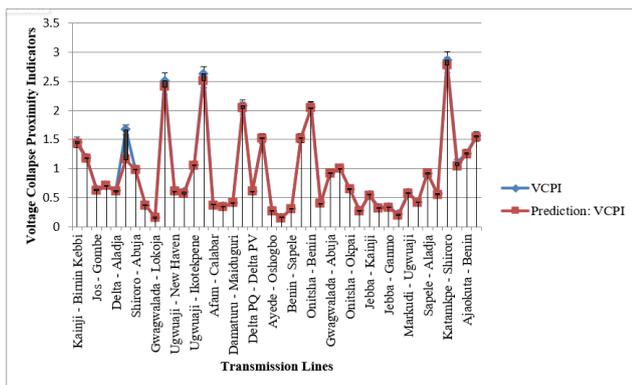


Figure 8: The calculated value of Voltage Collapse Proximity Indicator VS the Predicted Values for the training data

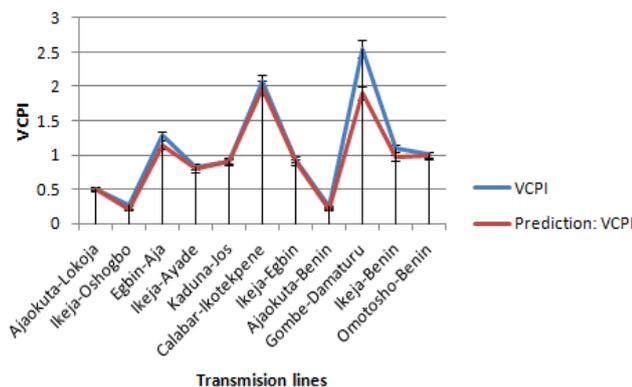


Figure 9: The calculated value of Voltage Collapse Proximity Indicator VS the Predicted Values for the tested data

4.0 CONCLUSION

It is thus proposed that the single topology artificial neural network be used for voltage collapse prediction. A single topology-based ANN has been developed to address the uncertainty surrounding the choice of the number of hidden layer neurons for voltage collapse prediction. The first trial of selecting the hidden layer neurons at the range of 10-100 neurons yields 0.05 RMSE. The result of the

simulation was validated on Nigerian power system network when the range was reduced from 10-65 hidden layer neurons. The result of the simulation using ANN portends best performance of 0.0091068 with optimally selected hidden layer neurons. The estimation of the hidden layer neurons aided in getting around under-fitting and over-fitting of data. The validation of the results when the script was tested with the second range of neurons shows that the approach is very effective for any kind of prediction or load forecasting. Since the Bayesian regularized technique proved to be the most accurate and efficient algorithm among the exploited training functions, it is proposed for the single topology artificial neural network for voltage collapse prediction.

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