VOLTAGE STABILITY ANALYSIS OF LOAD BUSES IN ELECTRIC POWER SYSTEM USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) AND PROBABILISTIC NEURAL NETWORK (PNN)

Ahmad Fateh Mohamad Nor, Marizan Sulaiman, Aida Fazliana Abdul Kadir and Rosli Omar
Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, Durian Tunggal, Melaka, Malaysia
E-Mail:ahmadfatehmohamadnor@gmail.com

ABSTRACT

This paper presents the application of neural networks for analysing voltage stability of load buses in electric power system. Voltage stability margin (VSM) and load power margin (LPM) are used as the indicators for analysing voltage stability. The neural networks used in this research are divided into two types. The first type is using the neural network to predict the values of VSM and LPM. Multilayer perceptron back propagation (MLPBP) neural network and adaptive neuro-fuzzy inference system (ANFIS) will be used. The second type is to classify the values of VSM and LPM using the probabilistic neural network (PNN). The IEEE 30-bus system has been chosen as the reference electrical power system. All of the neural network-based models used in this research is developed using MATLAB.

Keywords: voltage stability analysis, voltage and load power margin, artificial neural network, probabilistic neural network, ANFIS.

1. INTRODUCTION

Power system blackouts have been one of the major problem faced by electric utility companies around the world. Most of the previous power system blackouts that happened worldwide were caused by voltage instability [1], [2]. Voltage instability occurred whenever power system is not able to maintain the voltage magnitude at all buses remain the same after the power system is being exposed to a disturbance [3]-[5].Thus, voltage stability analysis is very useful in order to make sure that the voltage magnitudes at all buses in the power system do not reach unstable values.

Power-voltage (PV) curve and reactive power-voltage (QV) curve is one of the famous methods in analysing voltage stability[1], [6]. These curves are generated by a series of power flow. For every series of power flow, the load of the system is increased until the point where the system is not able to run anymore. The variation values of real power (P) and reactive power (Q) with the value of load is plotted as the PV and QV curve, respectively. PV and QV curve is very useful to obtain the values of voltage stability margin (VSM) and load power margin (LPM). Both VSM and LPM are needed in voltage stability analysis. This is because both VSM and LPM depict the distance of how far the power system is able to run before experiencing voltage instability[3], [7], [8].

Previous researches has successfully applied artificial neural network (ANN) in voltage stability analysis. However, it can be seen in the literature that only one type of ANN which is the multilayer perceptron backpropagation (MLPBP) is being applied[8]-[11]. In this paper, three types of ANN which are multilayer perceptron backpropagation (MLPBP) neural network, adaptive neuro-fuzzy inference system (ANFIS) and probabilistic neural network (PNN) are appliedin voltage stability analysis. MLPBP neural network and ANFIS are chosen for predicting the values of VSM and LPM. Meanwhile, PNN is applied to classify the values of VSM and LPM. The actual calculated values of VSM and LPM will be compared with the predicted values from ANN.

2. METHODOLOGY

2.1 Voltage Stability Margin (VSM)

Voltage stability margin (VSM) is defined as the distance between the normal/initial voltage operating point until the voltage critical/collapse point. VSM can be divided into two categories which are VSM for real power of load (P) and VSM for reactive power of load (Q). VSM (P) and VSM (Q) are obtained from PV and QV curve as shown in Figure 1[4], [5], [7], [8], [12]. It can be seen that the smaller value of VSM, the closer the bus of the power system towards voltage instability and vice versa. VSM can be depicted by using Equation(1) [7]:

$$VSM = \text{hypotenuse distance} \mid v_{initial} - v_{critical} \mid \qquad (1)$$

where,

$V_{initial}$ is the bus voltage at normal operating point
$V_{critical}$ is the bus voltage at voltage collapse point

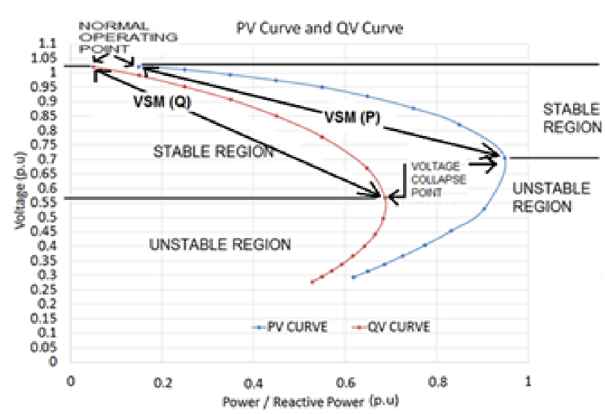

Figure-1. PV and QV curve.

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2.2 Load Power Margin (LPM)

Similar to VSM, load power margin (LPM) can be divided into two categories which are LPM for real power of load (P) and LPM for reactive power of load (Q).LPM (P)shows the distance of the real power (P) of load from the normal voltage operating point until the voltage collapse point as depicted in Figure-2 [7]. Equation (2) is useful for calculating LPM (P)[8].

$$LPM\ (P) = (P_{critical} - P_{initial}) \quad (2)$$

where,

$P_{critical}$ is the value of load (MW) at voltage collapse point

$P_{initial}$ is the value of load (MW) at normal operating point

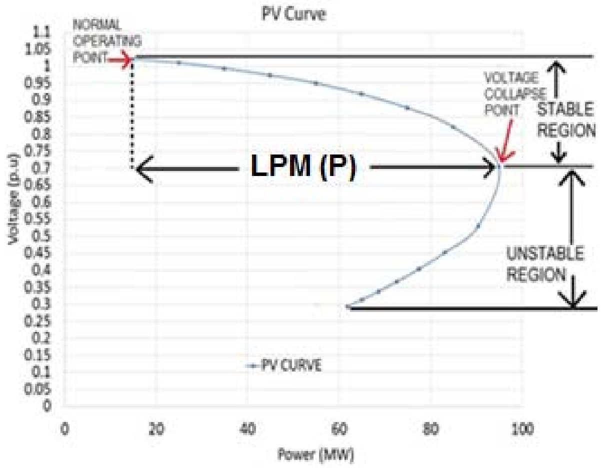

Figure-2. LPM (P) in PV curve.

LPM (Q) on the other hand is used to measure the distance of the reactive power (Q) of load from the base voltage operating point until the voltage critical point as shown in Figure-3 [13]. Equation (3) can be used to calculate LPM (Q)[13].

$$LPM\ (Q) = (Q_{critical} - Q_{initial}) \quad (3)$$

where,

$Q_{critical}$ is the value of load (MVAR) at voltage collapse point

$Q_{initial}$ is the value of load (MVAR) at normal operating condition.

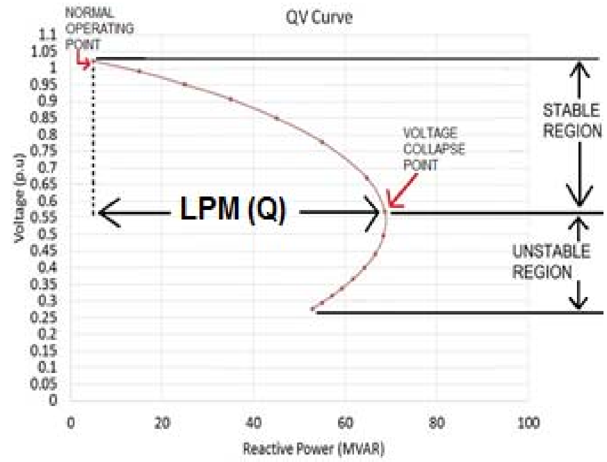

Figure-3. LPM (Q) in QV curve.

2.3 Artificial Neural Network (ANN)

Type 1: Predicting VSM and LPM Values

The ANN model will be used in this approach to predict the values of VSM and LPM. Two ANN types which are the MLPBP ANN model and ANFIS model are chosen for this task.

MLPBP networks are the most widely used of ANN model especially in data predictions, forecasting, pattern recognition and others [3], [8], [9], [14], [15]. In this approach, an optimised MLPBP model is used to predict the values of VSM (P), VSM (Q), LPM (P) and LPM (Q). The inputsof the optimized MLPBP model for both VSM (P) and VSM (Q) predictions are the values of $V_{initial}$, $V_{critical}$, load at normal operating point and load at collapse point. These values can be obtained in the PV and QV curve. Figure-4 depicts the optimised MLPBP model. MATLAB is used to run the optimized MLPBP model as shown in Figure-5.

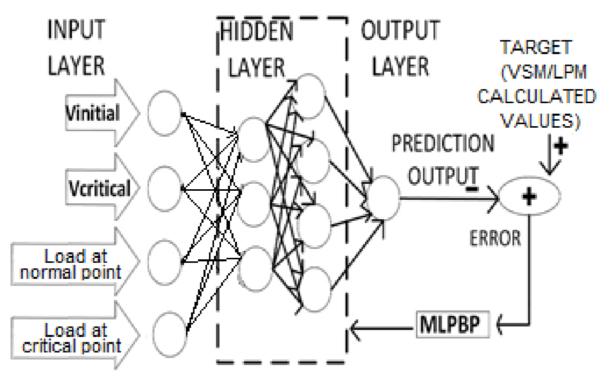

Figure-4. Optimised MLPBP ANN model.

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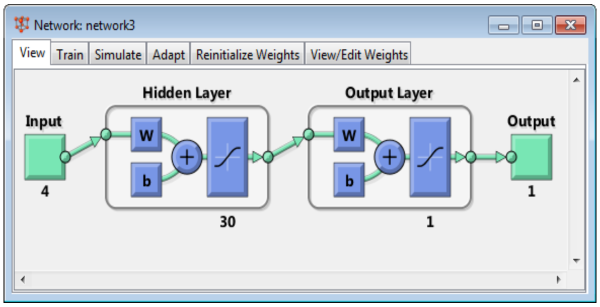

Figure-5. Optimised MLPBP ANN model in MATLAB.

Adaptive Neuro-Fuzzy Inference System or ANFIS is an architecture that consists a combination of ANN with Sugeno typed fuzzy logic. In ANFIS system, the ANN method such as backpropagation is used to improve the membership functions and rules of the fuzzy system[16], [17]. Figure 6 [16] shows the basic ANFIS structure.

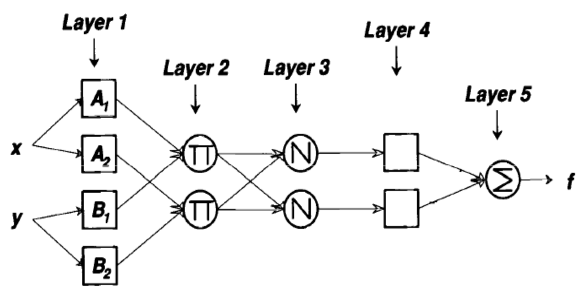

Figure-6. Basic ANFIS structure.

Figure-6 depicts that there are five layers in an ANFIS structure. The first layer consists of the fuzzy's membership functions. At the second layer, the minimum value of two input weights from the first layer is chosen. Then, the chosen weights are normalised in the third layer. The fourth layer contains linear functions of the input signals. Finally, the fifth layer sums all the incoming signals to produce final output [16], [17].MATLAB is used to run the ANFIS as shown in Figure-7.

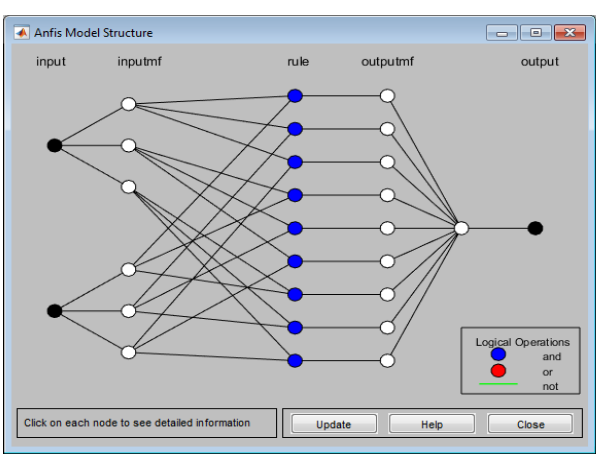

Figure-7. ANFIS structure simulated in MATLAB.

Type 2: Classification of VSM and LPM values

In this research, probabilistic neural network (PNN) is used to classify the calculated values of VSM and LPM. According to [18], PNN is best used for classification purposes. Figure-8 shows the basic PNN structure [18]-[20].

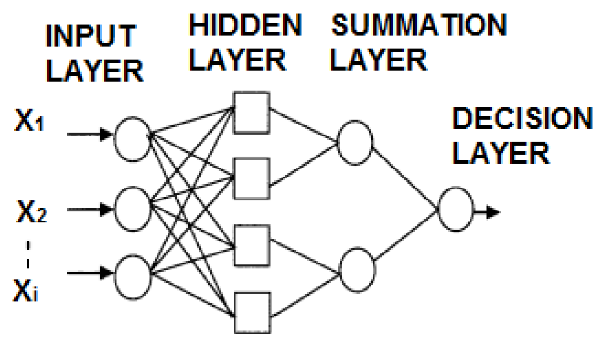

Figure-8. Basic PNN structure.

Basically, PNN has four layers. The input layer will be the data that need to be classified (in this research, the calculated values of VSM and LPM). Then, the hidden layer calculates the distance measure between the input test case and the centre of training case represented by the neuron. In the summation layer, the density function of which classthe hidden outputs layer belong to is estimated. Finally, at the decision layer, the class thatobtains the higher probability in the summation layer are selected [18]-[20].

The calculated values of VSM and LPM are classified into five classes. Class 1 denotes the lowest values of VSM/LPM which is the most critical values. Class 5 will represent the largest values of VSM/LPM which represents the safest buses. The classification data for the PNN is listed in Table-1.

Table-1. Classification data for the PNN.

	Class 1	Class 2	Class 3	Class 4	Class 5
VSM (P)	≤ 0.5	≤ 1.5	≤ 2.5	≤ 3.5	≤ 4.5
VSM (Q)	≤ 0.5	≤ 1.0	≤ 1.5	≤ 2.5	≤ 3.5
LPM (P)	≤ 50	≤ 150	≤ 250	≤ 350	≤ 450
LPM (Q)	≤ 50	≤ 100	≤ 200	≤ 300	≤ 400

2.4 The IEEE 30-bus system

Figure-9 illustrates the IEEE 30-bus system [21]. In this system, Bus 1 is the slack bus, Bus 2, Bus 5, Bus 8, Bus 11 and Bus 13 are voltage controlled buses, and the rest buses (Bus 3, Bus 4, Bus 6, Bus 7, Bus 9, Bus 10, Bus 12, and Bus 14 until Bus 30) are load buses. Load buses are very important in voltage stability analysis because PV and QV curve are generated at load buses. The load flow

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analyses are done by using Power World Simulator software version 16.

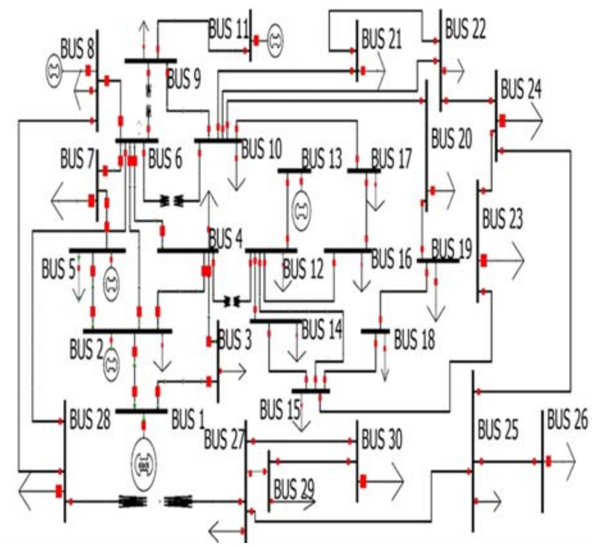

Figure-9. IEEE 30-bus system.

3. RESULTS AND DISCUSSIONS

It was found from the previous works that voltage stability modal analysis technique showed that the weakest buses are Bus 26, Bus 29 and Bus 30 [5], [22], [23]. Therefore, more attention are given to these buses in the following results.

3.1 Type 1results: predicting VSM and LPM values using MLPBPANN and ANFIS

The predicted VSM and LPM values by MLPBP ANN and ANFIS are recorded and being compared with the actual calculated VSM and LPM values. The results are illustrated in Figure-10, Figure-13.

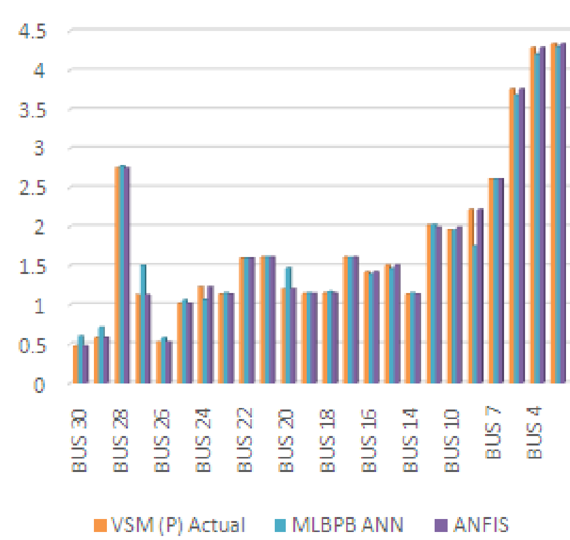

Figure-10. Comparison between the actual, MLPBP ANN and ANFIS predicted values of VSM (P).

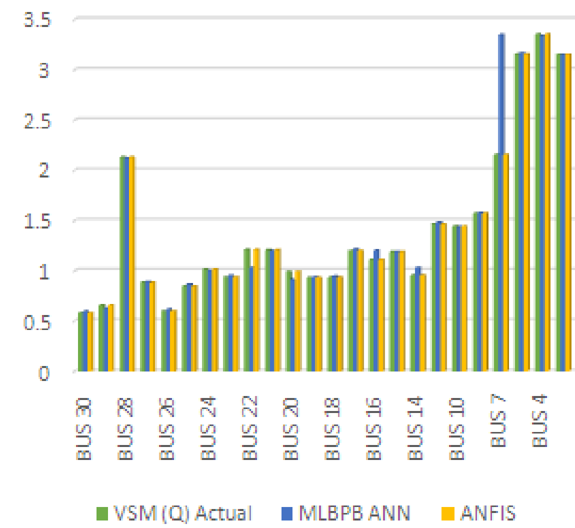

Figure-11. Comparison between the actual, MLPBP ANN and ANFIS predicted values of VSM (Q).

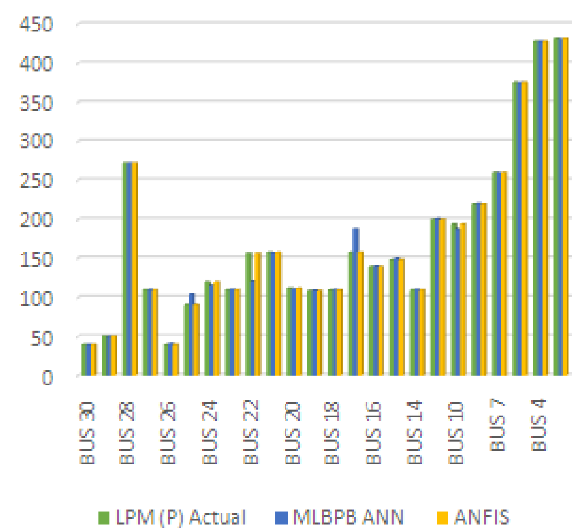

Figure-12. Comparison between the actual, MLPBP ANN and ANFIS predicted values of LPM (P).

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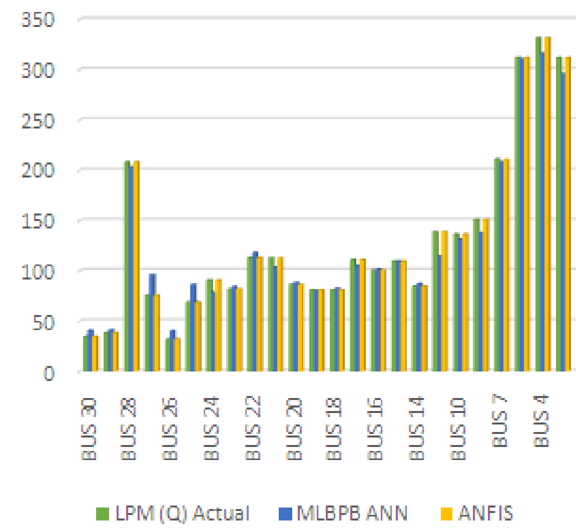

Figure-13. Comparison between the actual, MLBPB ANN and ANFIS predicted values of LPM (Q).

Figure-10, Figure-11, Figure-12, and Figure-13 show that Bus 26, Bus 29 and Bus 30 are the buses with the lowest values of VSM (P), VSM (Q), LPM (P) and LPM (Q), respectively. The results have predictedthat VSM and LPM values from MLBPB ANN and ANFIS are very close to their corresponding actual calculated values. However, it is noticeable that ANFIS yields much closer predicted values to the actual values compared to MLBPB.

3.2 Approach 2: classification of VSM and LPM Values using PNN

The results of classification of VSM and LPM values using PNN and its comparison with the actual classification specified in Table-1are shown in the Figure-14, Figure-17.

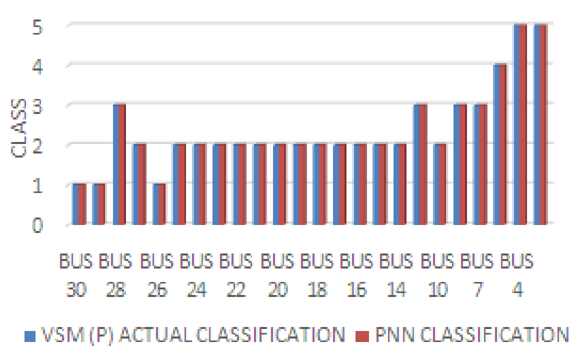

Figure-14. Comparison between the actual and PNN classification of VSM (P).

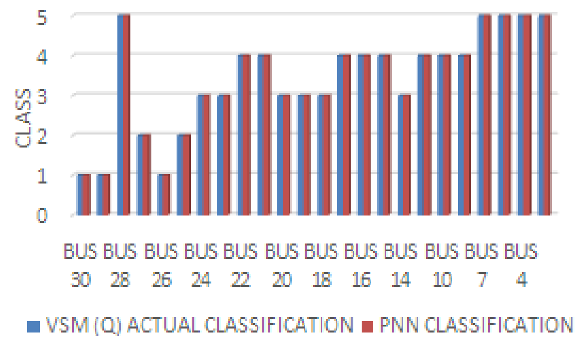

Figure-15. Comparison between the actual and PNN classification of VSM (Q).

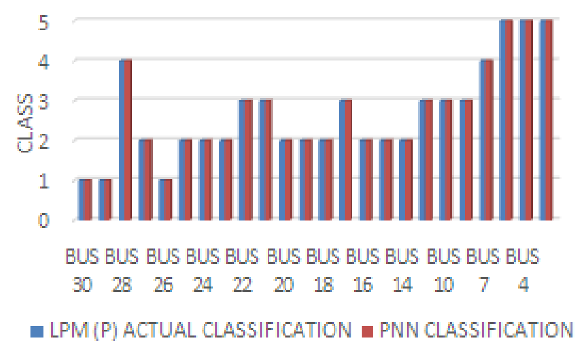

Figure-16. Comparison between the actual and PNN classification of LPM (P).

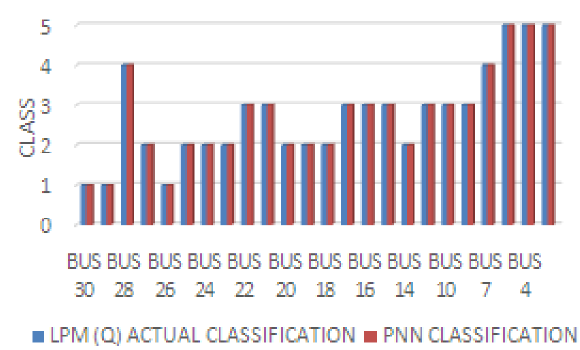

Figure-17. Comparison between the actual and PNN classification of LPM (Q).

It has been shown from Figure-14 until Figure-17 that PNN has ample capability to classify the values of VSM and LPM according to the actual classification specified in Table-1. Those figures also show that Bus 26, Bus 29 and Bus 30 belong to Class 1. Buses in Class 1are inclined towards experiencing voltage instability because of low values of VSM and LPM.

4. CONCLUSIONS

The research conducted in this paper has successfully utilised various types of artificial neural network to analyse voltage stability especially in

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predicting and classifying the values of VSM and LPM. In terms of predicting the VSM and LPM values, ANFIS produced more accurate values compared to MLBPB ANN. This shows that the combination of ANN and fuzzy algorithm inside the ANFIS structure is useful in producing more accurate results. In terms of classifying the VSM and LPM values, PNN has carried out the task successfully. The aptitude to foresee voltage instability are paramount so that precautions measures can be taken to avoid voltage collapse.

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