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Multibus Power Transmission System's Voltage Stability Limit Prediction Using Artificial Neural Network

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Abstract

The objective of this paper is to predict the voltage stability limit of a multi-bus power transmission system using Artificial Neural Networks (ANN). When a system is overloaded or a change in the systems condition, there is an uncontrollable drop or collapse of voltage occurs. The weakest, weaker, and weakest bus in the IEEE - 30 bus systems can be identified by using the Newton Raphson method of load flow analysis. The IEEE 30 bus system is simulated using MATLAB programming. In the Jacobian matrix of the said system, there are four sub matrixes that are J1, J2, J3 and J4. By using the values of diagonal elements of J4 matrix, dq / dv of the load buses has been calculated and inverted these values to find the dv/dq index for finding out the weak segment of the network. Finding the critical bus voltage magnitude and active power loading values is the goal of the study's second phase. Plotting the PV curve of the matching buses is how this is accomplished. For this reason, the weakest bus active power loading has been gradually increased while the active power loading of the other buses has remained constant. The goal of the paper's final page was to use an artificial neural network (ANN) to discover the crucial bus voltages for any unforeseen loads. In this case, a multilayer feed forward network and a back propagation algorithm were used to determine the critical voltage magnitude values.

Keywords: Voltage Stability, Reactive power sensitivity indicator, Artificial Neural Network

1. Introduction

Because of economic restrictions, power systems are being run closer to their stability limits these days. Maintaining a steady and safe power system functioning is thus a difficult and critical topic. Voltage stability refers to the capacity of the power system to maintain steady state voltages at all buses after being subjected to a disturbance from a certain beginning operating point. Voltage stability in the power system refers to a power system's ability to maintain suitable voltages at all of its bus in ideal conditions and after a disruption. When a power system is functioning properly, the voltage is steady. When a malfunction or other interruption occurs, the voltage becomes unstable, resulting in a steady and unabating decline in voltage. Voltage stability is also known as load stability.

In a certain operating condition, when the reactive power injection at the same bus is increased, the bus voltage magnitude increases and the bus voltage is referred to as being voltage stable for that bus in the electrical systems. The magnitude of the bus voltage declines for at least one of the buses when the reactive power injection at one of the buses is increased, causing voltage instability in the system. When the VQ sensitivity is positive, stable system voltage is created for all buses, however when the VQ sensitivity is negative, unstable system voltage is produced for at least one bus. A power system may encounter a voltage collapse if the post disturbance equilibrium voltage near the loads is below allowable bounds. Total or partial blackouts may result from voltage collapse. The voltage collapse and the voltage instability are frequently used interchangeably. ANNs can model noisy, nonlinear, and dynamic data. The ANNs can quickly analyse the voltage stability and monitor it online. For ANNs to create a good system design, sophisticated programming, perplexing algorithms, and illogical inference techniques are not necessary. So, ANN-based systems are simple to implement. ANN handles dependent and independent variables that are randomly determined, and it only needs a little amount of information on the physical underpinnings of the process.

2. Materials and Methodology

2.1 Reactive Power Sensitivity Index

The basic which is used in the Newton-Raphson Load Flow Analysis is asfollows

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_1 & J_2 \\ J_3 & J_4 \end{bmatrix} \begin{bmatrix} \Delta \delta \\ \frac{\Delta V}{|V|} \end{bmatrix} \quad \ldots\ldots\ldots\ldots\ldots\ldots..(1)$$

Here '**J**' is the Jacobian Matrix, which is consists of J_1, J_2, J_3 and J_4. The reactive power sensitivity indicated by the diagonal elements of J_4.

The Diagonal and the OFF-Diagonal components of J4 are -

$$\frac{\partial Qi}{\partial|\mathrm{Vi}|} = -2\ |Vi|\ |Yii|\ \sin(\emptyset ii)\ - \sum_{j=i}^{n} |Vj|\ |Yij|\ \sin(\emptyset ij - \delta i + \delta j) \quad \ldots\ldots\ldots\ldots\ldots\ldots..(2)$$

$$\frac{\partial Qi}{\partial|\mathrm{Vj}|} = -|Vi|\,|Yij|\,\sin(\emptyset ij - \delta i + \delta j);\ \ i \neq j \quad \ldots\ldots\ldots\ldots\ldots\ldots..(3)$$

The value of dQ/dV for each load bus can be determined from equation (2), the diagonal element of J4, and by calculating the inverse of this value, we can get the reactive power sensitivity of any given bus.

The strongest and weakest bus can be identified using the reactive power sensitivity index, often known as the dV/dQ index. The bus is recognized as the strongest bus when the dV/dQ index is at its lowest value. On the other side, the bus might be referred to as the weakest bus when the dV/dQ index is highest.

2.1.1 Benefits of Reactive Power Sensitivity Index:

i. Reactive Power Sensitivity Indicator improves the voltage stability ofthe system.
ii. Reactive power seeks to minimize the congestion of power flow.
iii. It reduces the power losses.
iv. Reactive power is essential to move active power through thetransmission line.

2.2 The Artificial Neural Network applications

The standard load flow analysis will take less time to compute if Artificial Neural Networks are used to anticipate the crucial values of active power loading and bus voltage magnitude. The trained artificial neural network will instantly offer the bus voltage magnitude for any active power loading that is not yet visible after sufficient training. In this research, a back propagation method and a feed forward neural network were used.

2.2.1 Architecture of Feed Forward Network

Moving forward Artificial neural network nodes that are known as neural network nodes do not form loops. Due to the fact that all inputs are simply transferred forward in this sort of neural network, it is also referred to as a multi-layer neural network. Data flow involves the receipt of data at input nodes, transmission across covert layers, and output at nodes. There are no linkages in the network that could be manipulated to convey data back from the output node. The following functions are approximated by a feed-forward neural network:

Classifiers are computed by an algorithm utilising the formula y = f*(x).

Therefore, category 'y' is given to input 'x'.

The feed forward model states that y = f (x;). The function's closest approximation is determined by this value.

2.2.2 Single Layer and Multi-Layer Network

The idea of an ANN with just one weighted layer. In other words, we can say that the input layer and output layer are totally coupled. A layer's nodes are all connected to the nodes of the layers below it, with varying weights placed on the connections. The signal layer can only go in one direction, from input to output, because there is no feedback loop. Fig.2.1 shows the single layer network.

The idea of an ANN having many weighted layers. This network is known as having hidden layers because there are one or more layers between the input and output layers. Fig.2.2 shows the multi-layer network.

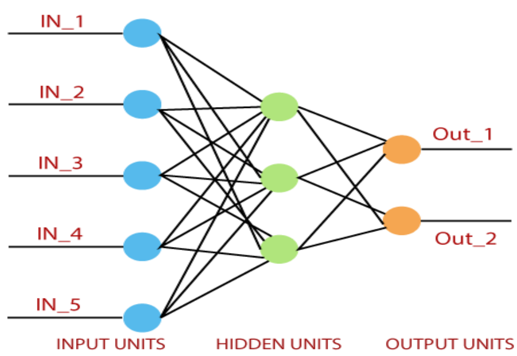

Figure 2.1 Single Layer Network

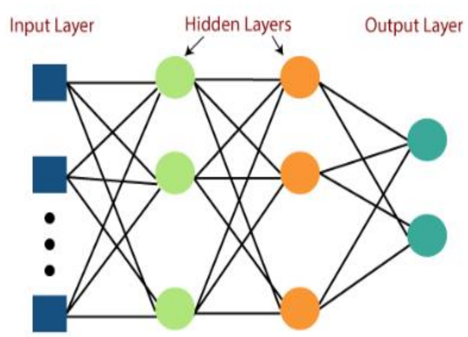

Figure 2.2 Multi - Layer Network

2.2.3 Backpropagation algorithm

Backward propagation of mistakes, also known as backpropagation, is a technique designed to detect errors as they move backward from input nodes to output nodes. It is an essential mathematical tool for data mining and machine learning to boost the accuracy of forecasts. Backpropagation is a technique for quickly calculating derivatives. Typically, backpropagation networks can be divided into two groups. A static back propagation is used to convert static inputs into static outputs. For fixed-point learning, the recurrent backpropagation network is employed. The activation of recurrent backpropagation propagates until it reaches a fixed value.

3. Result and simulation

The Newton Raphson method of load flow analysis can be used to determine which bus in the IEEE - 30 Bus systems is the weakest. Additionally, the weak and weaker buses of the system under investigation may be located. The IEEE 30 bus system is simulated using MATLAB programming. In the IEEE – 30 bus systems, 5 numbers of buses are voltage-controlled buses, among which two buses are converted to PV buses because of their Q limits. In the Jacobian matrix of the said system there are four sub matrixes that is J1, J2, J3 and J4. By using the values of diagonal elements of J4 matrix, dq/dv of the load buses has been calculated and inverted these values to find the dv/dq index for finding out the weak segment of the network. Finding the critical bus voltage magnitude and active power loading values is the goal of the study's second phase. Plotting the PV curve of the matching buses is how this is accomplished. To achieve this, the active power loading of the weakest bus has been gradually increased while maintaining the base loading of the other buses. The goal of the project work's final page was to use an artificial neural network (ANN) to discover the crucial bus voltages for any unforeseen loads. In this case, a multilayer feed forward network and a back propagation algorithm were used to determine the critical voltage magnitude values.

3.1 Determination of Weakest bus of IEEE- 30 Bus system

Both straightforward systems and extensive power system networks can be used to study voltage stability. The computation of the lowest Eigenvalues and Eigenvectors of the Jacobian matrix, which was reduced and derived from the power flow solution, is one of the crucial steps in this process. A relative indicator of the proximity to voltage instability can be obtained from the predicted eigenvalues' links to a voltage amplitude and reactive power variation mode. The bus in the system that is the weakest, weaker, and weakest can subsequently be identified by computing the participation factor. Reactive power sensitivity index has been used to determine which bus in the IEEE 30 bus system is the weakest. In MATLAB software, a load flow study employing the Newton-Raphson method has been created for this purpose. The Jacobian matrix of the system under study was ascertained from the programming's output. Each load bus's dq/dv value has been calculated using the diagonal elements of sub matrix J4. As a result, the sensitivity index (dv/dq) for each load bus has been determined by calculating the reciprocal of dq/dv, and the results are shown in Table number 3.1

Table – 3.1 Stability Ranking

Bus Number	dv/dq
2	0.3352
3	0.0342
4	0.0178
5	0.2763
6	0.0119
7	0.0543
8	0.0437
9	0.0506
10	0.0230
11	0.1030
12	0.0382
13	0.5572
14	0.1750
15	0.0596
16	0.1118
17	0.0654
18	0.0976
19	0.0541
20	0.0615
21	0.0215
22	0.0223
23	0.1394
24	0.1067
25	0.1249
26	0.1234
27	0.1813

According to Table 5.1, bus number 13 is the network's weakest bus since its dq/dv value is 0.5572, which can be seen as a result. Similar to this, the networks' weaker and stronger buses are designated as buses 2 and 5, respectively.

3.2 Determination of the Critical values of Power (P) and Voltage (V) of the weakest, weaker and weak bus PV curve

After finding the weakest segments of the network, the critical values of bus voltage magnitude and active power loading has been determined using PV curve. For this purpose, PV curves of bus number 13, 2 and 5 are plotted. The active power loading of the relevant bus has been gradually increased while the loading of other buses has remained constant for the purpose of plotting PV curves. Accordingly, more than 300 numbers of bus voltage magnitudes have been determined for the corresponding active power loading upto the stability limit of the bus, which are used for the plotting of PV curves. The PV curves of bus number 13, 2 and 5 are shown in figure number 3.1, 3.2 and 3.3 respectively.

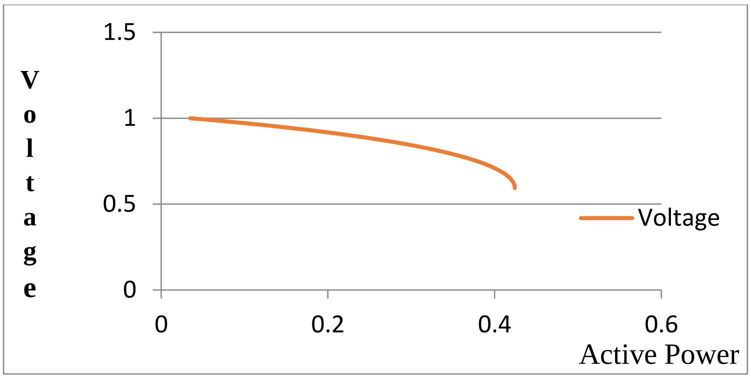

Figure 3.1: PV curve of bus no. 13 (Weakest Bus)

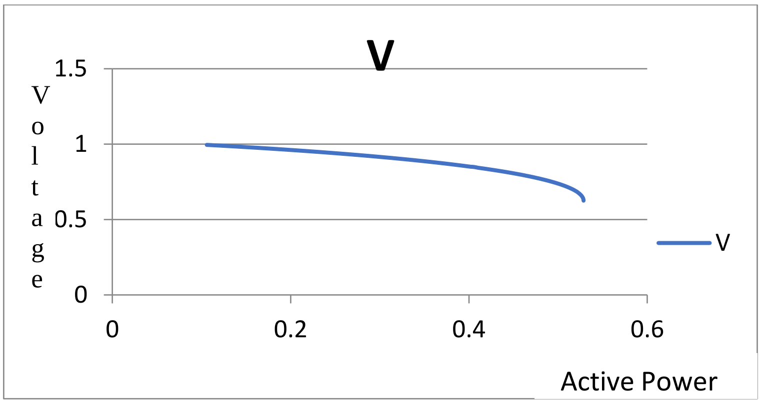

Figure 3.2: PV curve of bus no. 2 (Weaker Bus)

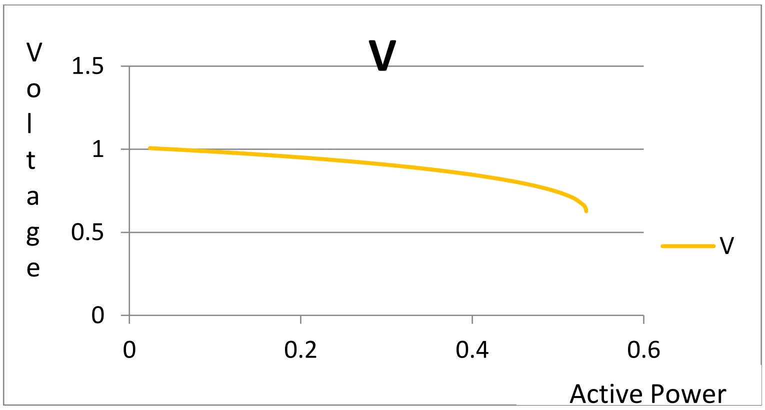

Figure 3.3: PV curve of bus no. 5 (Weak Bus)

From the above PV curves, the critical values i. e. the values of bus voltage magnitude and active power loading at the stability limit of the corresponding buses has been determine and tabulated in table number 3.2, for example the critical voltage of bus no. 13 is 0.5935 corresponding to the active power loading value 0.4241634346.

Table 3.2

Bus Number	V_{cri}	P_{cri}
13 (Weakest)	0.5935	0.4241634346
2 (Weaker)	0.6252	0.52856895
5(Weak)	0.6271	0.532884752

From the table number 3.2, it is clearly observed that the bus voltage magnitude of bus number 13, i. e. the weakest bus is highly depressed compared to the weaker and weak buses. Additionally, it has been noted that bus number 13 has a far lower critical value for active power loading than the other buses. This result also supports the reactive power sensitivity indicator (dv/dq)-based load bus ranking of the study network reported in table no. 3.1.

3.3 Prediction of bus voltage using ANN for different loading at the weakest bus

In the second phase of the work, ANN has been used for the prediction of bus voltage magnitude for any unseen active power loading.

3.4 Data preparation for training

The training data set comes from a load flow system that accounts for every imaginable loading scenario. Bus voltage magnitudes are noted under all possible loading and used as target output for training purpose. For this purpose more than 300 samples of data are obtained, out of which more than 280 was used for training and 10 numbers of data has been used for the testing. Any numbers of sample data can be used for the training and as well as testing using ANN.

3.5 Application of ANN for predicting bus voltage magnitude

Here, active power loading has been used as an input data and corresponding values of bus voltages are used as an target output. In this case more than 280 numbers of input output data has been used for training purpose as mentioned above. After proper training it is observed that the said ANN is capable of delivering the target outputs with high accuracy as depicted in fig.3.4. Here it is seen that all the outputs are lies on the curve after proper training. The error curve for this training is shown in fig. 3.5.

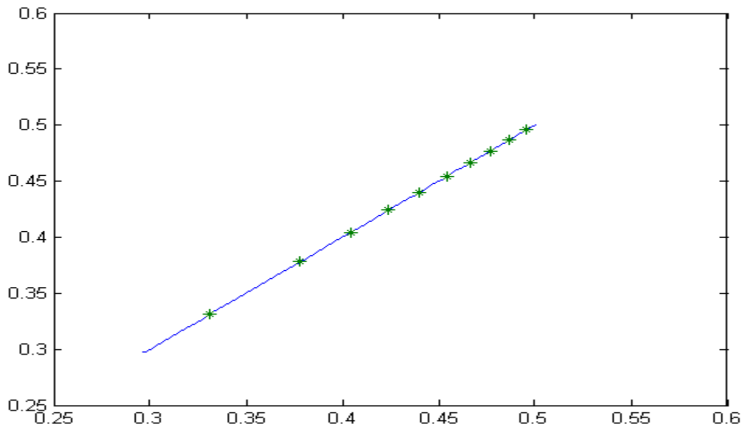

Figure 3.4 (Graph after training)

Error curve:

The fig. 5.4 shows the error curve between the Mean Squared Error (mse) and epoch. After 1000 epoch, it is seen that the error is nearly zero. In the graph, the blue colour shows the train and the dotted line shows the best performance.

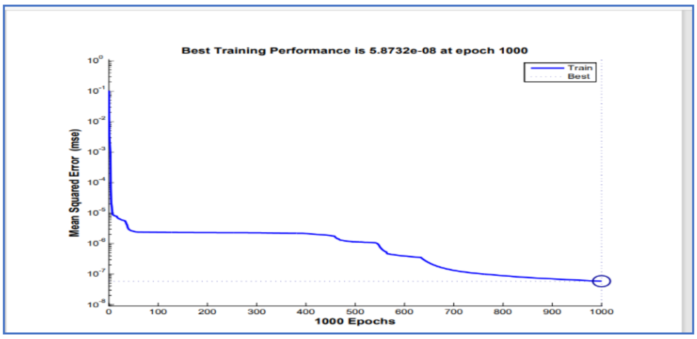

Figure 3.5 (Error Curve)

3.6 Error calculation for output data generated by the ANN

From table 3.3, it is observed that, the target output that is the bus voltage magnitudes for different active power loading as generated by the ANN is almost actual values. The percentage of error is shown in the last column of the table which shows the percentage errors is varies from 0 to 0.0429 and the maximum error is -0.0429 and the minimum error is 0, which proves the effectiveness of the proposed work. The fig 3.6 shows the graph between corresponding values of the bus voltage generated by ANN and the original values of the bus voltage magnitudes for 10 numbers of active power loading sample data. From this figure it is observed that the curve of voltage magnitudes generated by the ANN for unseen loading almost overlap with the original voltage magnitude curve, which demonstrate the accuracy of the result generated by the ANN. Figure 3.7 shows the graph of percentage of error between the original bus voltages and the voltage generated after testing of 10 numbers of sample data of bus no. 13.

Table 3.3

Case Number	Input Active Power Loading of Bus No. 13	Corresponding values of bus voltage generated by ANN	Original value of the bus voltage	Percentage of Error
1	0.055	0.9920	0.9919	0.0101
2	0.095	0.9740	0.974	0
3	0.135	0.9543	0.9544	-0.0105
4	0.175	0.9324	0.9328	-0.0429
5	0.215	0.9081	0.9082	-0.011
6	0.255	0.8805	0.8804	0.0114
7	0.295	0.8479	0.8479	0
8	0.335	0.8085	0.8085	0

9	0.375	0.7562	0.7564	-0.02644
10	0.416	0.6622	0.6621	0.0151

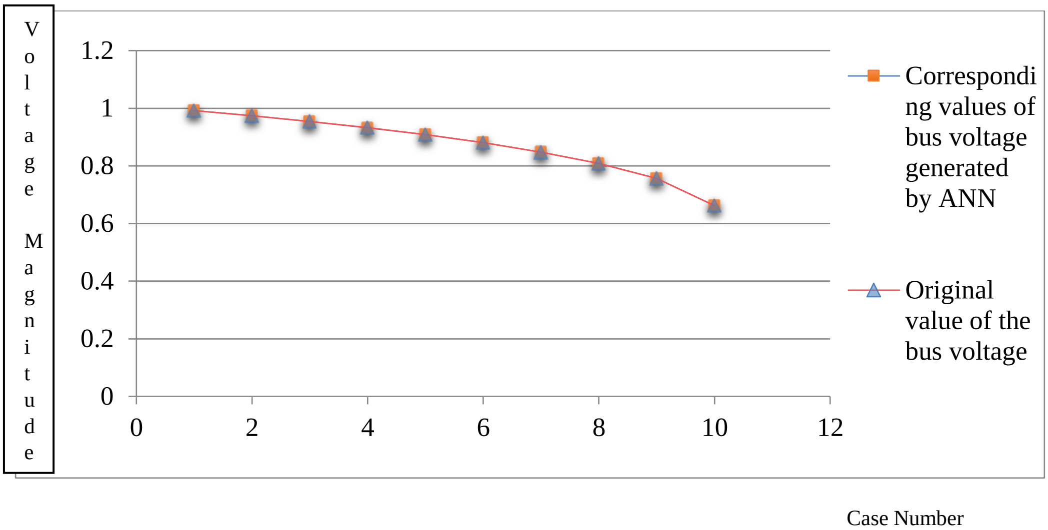

Fig. 3.6 (The graph of corresponding values and original values of the bus voltage)

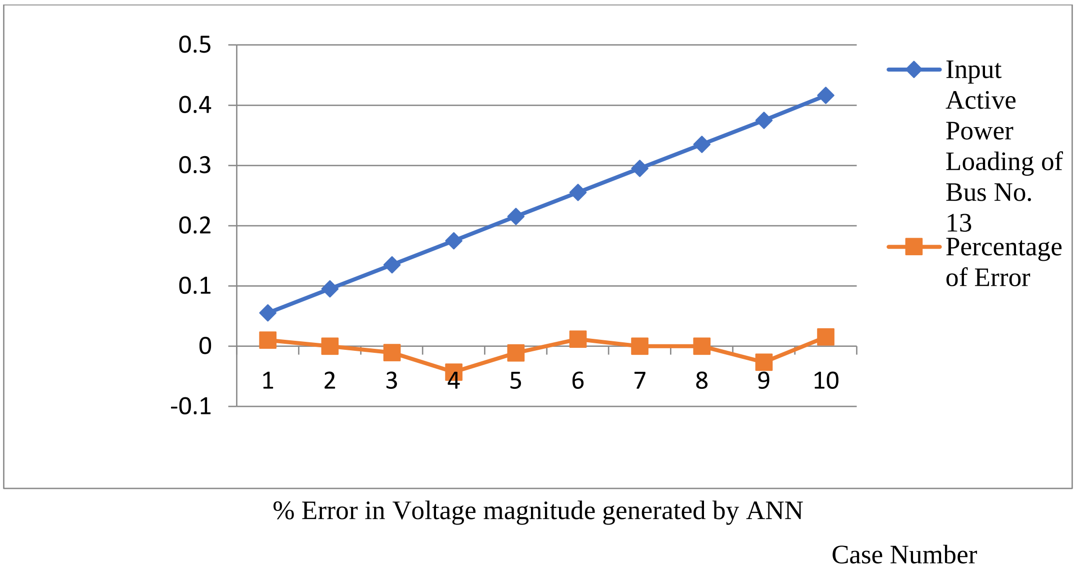

Fig. 3.7 (Error graph after the calculation)

4. Conclusion

The weakest area of the IEEE 30 bus network has been identified using the reactive power sensitivity indicator, and the key active power loading values and associated bus voltage magnitude have also been found using the PV curve approach. To save the computational time of conventional load flow analysis, here ANN is applied for the prediction of bus voltage magnitude for any unseen loading of active power. The results show that the trained ANN can produce the intended output with excellent accuracy. This method can help the operator at the control centre for taking necessary action based on the output generated by the ANN.

REFERENCES:

1. Kabir Chakraborty, Gitanjali Saha, Priyanath Das (2018), “Voltage stability prediction on power networks using Artificial Neural Network” International Journal of Electrical Engineering and Computer Science, vol-10, pp 1-9.
2. D. Q. Zhou, U. D. Annakkage, A. D. Rajapakse (2010), “Online monitoring of voltage stability margin using an artificial neural network”, IEEE Transections on Power Systems, vol:25, PP 1566-1574.
3. Kabir Chakraborty, Sangita Das Biswas (2007), “An offline simulation method to identify the weakest bus and its voltage stability margin in a multibus power Network”, Proceeding of International Conference.
4. K. Selvakumar, C. S. Boopathi, M. Sri Harsha (2016), “Voltage stability assessment using Artificial Neural Networks”, Indian Journal of Science and Technology, vol 9(38),
5. Kabir Chakraborty, Bijaya Saha, Satwati Das (2015), “A method for improving Voltage stability of a Multi-bus Power System Using Network Reconfiguration Method”, International Journal of Electrical Engineering, vol 8, pp. 91-102
6. Kabir Chakraborty, Abhinandan De, Abhijit Chakrabarti (2012), “Voltage stability assessment in power network using self-organizing feature map radial basis function”, Computers and Electrical Engineering, vol 38, pp.819-826.
7. A. R. Bahmanyar, A. Karami (2014), “Power system voltage stability monitoring using artificial neural networks with a reduced set of inputs”, Electrical Power and Energy System.
8. Shantasree Roy, Madhabi Jamatia, Sangita Das Biswas (2013), “Determination of Voltage Stability Using Sensitivity Indicator”, International Journal of Electronics communication and Computer Engineering, vol 4, print 2278-4209.
9. Dhiraj Tikar,. Pankaj Ambilduke, Priya Patil (2018), “Literature review on Improvement of Voltage Stability by using Static Var Compensator”, IJEDR 2018, vol 6.
10. Subir Datta, Anjan Kumar Roy (2012), “ANFIS based 48-pulse STATECOM Controller for Enhancement of Power System Stability”, International Journal of Modelling and Optimization, vol. 2.