Voltage Security Margin and Load Limit of the System by Artificial Neural Network Method

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Abstract: In this paper, the artificial neural network method is used to deal with the system voltage stability problem for the system load limit. Voltage stability has long been an important issue in the study of power system stability and so far many methods have been used to evaluate and diagnose system stability. Different methods are used to compensate and stabilize the voltage system. However, evaluation and diagnosis still play a significant role in the stability of the voltage system. In this paper, the artificial neural network method is used to evaluate stability. Newton Raphson's load distribution is used to solve this model. Modelling and implementation of this paper have taken the pattern 30 BUS IEEE network test to show the efficiency of this paper.

Keywords: Artificial Intelligence, ANN, Voltage Stability, Newton Raphson, Load Ability Limit, MATLAB.

1. Introduction

Due to a surging demand for the power networks and quality-sensitive devices, the independent operator system is forced to provide quality energy and reliability in the networks for its loads. However, sometimes the network is unstable, and sometimes the voltage collapsed. Countries such as France [1] and the USA [2], have faced voltage collapse during last few years. Factors of instability in the power system consist of a sudden increase in load, severe clogged transmission lines, the lack of coordination of the protection system, which lead to instability and voltage collapse. Voltage stability is the ability of power system to preserve and maintain the range of its bus voltage from increasing used load; furthermore, it is emerged as a main concern for power system security and a limit for loading and power transfer. Over the past few years, many approaches have been taken including, reactive power compensation, using transformer, using protective equipment, and eventually load overflow, in order to tackle voltage stability problems. However, most of such compensation equipment is controlled automatically. Sometimes, system is unable to response to unnatural accidents which had not been predicted by the program. Thus, steady state voltage stability must be determined at any time so as to enable operator to response to natural disasters or the failure of protection system manually. There are some methods to determine the breakdown voltage point such as: Jacobi method, Quantity index, Impedance index, and Special index. But in these traditional methods, the calculations of load distribution take time. However, in power system dynamic analysis, time plays a key role. As a result, operators are of little time to figure out what has happened before the breakdown voltage occurs [3].

In this paper, voltage stability indexes are utilized for IEEE 30-Bus System to determine the impacts of active and reactive loads on the operation of voltage stability indexes. Stimulation is performed in MATLAB and the results will be indicated later in the following article.

2. Description of the Proposed Model

The model presented in this paper examines long-term voltage stability and system load limit. The ability of a power system to maintain the voltage range of its bus bars against increasing load is called static voltage stability. Increasing the load capacity of the power system, which represents the maximum load imposed on a power system, is considered as an indicator of assessing the degree of safety of the power system.

2.1. Types of voltage breakdown

2.1.1. Voltage collapse in the long run:

This type of breakdown occurs when generators and generators of electrical power are too far away from load sources and the transmission lines are overloaded. In addition to that, the system cannot provide acceptable voltage at the load sources. Voltage collapse can occur when the system cannot deliver enough reactive power to the load region. For instance, when the output is reduced. This voltage drop can last from a few minutes to a few hours. The consequences of collapse often require long system restoration, while a considerable number of customers are left without electricity supply for a long time. [4,6].

2.1.2. Classic voltage collapse:

This happens when in an interconnected power system with distributed generation, an error leads the system to disconnect and the power system does not have enough reactive power storage to meet the system needs and consumers' demand of load. The greater the reactive power shortage, the greater the voltage drop. Eventually, the voltage reaches a point in which it is not possible to return to the original state and the system collapses. This can happen between 1 and 5 minutes after the error occurs [5].

2.1.3. Transmit voltage collapse:

There are two types of collapse in this part, but both give less than 15 seconds after the disturbance. Rapid voltage breakdown can occur with reduced synchronism, or breakdown occurs when a large number of motors fail and they all want to return to the circuit together. This situation can lead to high reactive power consumption and voltage breakdown [6].

2.1.4. Voltage instability prediction solutions

2.1.5. Analysis by load flow

2.1.6. Voltage stability is dynamic. Load flow analysis is specific when a large amount of load is non-motorized. This method is used in a wide range of studies when voltage stability ranges for pre-and post-fault conditions must be determined. It has also been used successfully to troubleshoot the occurrence of real power systems. Following an error, or during an increase in load, the load flow analysis simulates a snapshot of the power system.

2.1.7. Analysis by time variable

In this analysis, time intervals for changing system parameters are considered.

2.1.8. Analysis by minimum value of Jacobin matrix of load distribution equations

The minimum eigenvalue of the Jacobin matrix of the load distribution equations at the point of voltage breakdown approaches zero. Therefore, this index can be used as a criterion to determine the load capacity of the system.

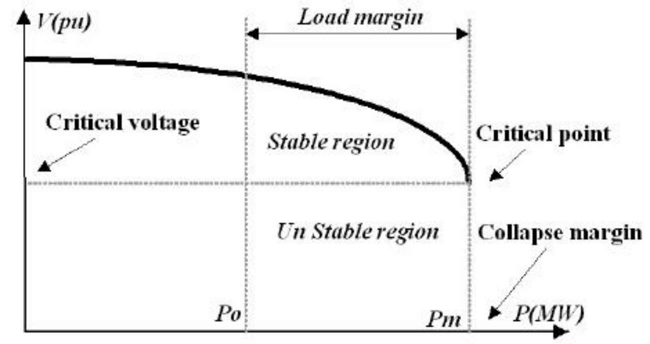

Fig 1: PV curve of a load bus in the power system[7].

ΔP : the change in the value of the active power
ΔQ: the change in the value of the reactive power
Ji : the elements of Jacobian matrix
$\Delta\delta$: the change in voltage angle
$\Delta|V|$: the change in voltage size

3. Newton Raphson Load Flow

The most well-known method for solving nonlinear equations is Newton-Raphson method. In this method, we start with an initial conjecture, then write the Taylor series for the equations and omit the higher degree terms. The result is that the nonlinear system becomes a linear system as follows. Where ΔP and ΔQ are calculated from the following equation: (1), (2)

$$\Delta Pi =- Pi + \sum_{k=1}^{n} |Vi||Vk|(Gik \sin\theta ik + Bik \cos\theta ik)$$

$$\Delta Qi =- Qi + \sum_{k=1}^{n} |Vi||Vk|(Gik \cos\theta ik - Bik \sin\theta ik)$$

In Newton-Raphson method, the number of repetitions to achieve the answer is less. The number of repetitions does not depend on the number of basses and the speed of the answer is high. This method is stable and often converges and the results obtained are more accurate [7].
The Jacobin matrix is calculated from the following equation (3)

$$J = \begin{bmatrix} H & N \\ J & L \end{bmatrix} \Rightarrow J = \begin{bmatrix} \frac{\partial \Delta \mathrm{P}}{\partial \theta} & \frac{\partial \Delta Q}{\partial |V|} \\ \frac{\partial \Delta}{\partial \theta} & \frac{\partial \Delta Q}{\partial |V|} \end{bmatrix} \qquad (3)$$

Angle values (4) and voltage size (5) are equal to:

$$\theta^{m+1} = \theta^{m} + \Delta\theta \qquad (4)$$

$$|V|^{m+1} = |V|^{m} + \Delta|V| \qquad (5)$$

3.1. Artificial Neural Network

ANN is a highly efficient computational tool that could be used for on-line load ability evaluation. The Artificial Neural Network (ANN) has been known as a powerful tool for function approximation and dynamic system control, owing to the advantage of high computational rate and unique learning capability. An ANN is based on a set of connected units or nodes, called artificial neurons, neurons usually have weights that are adjusted as learning progresses. Once the network is trained and tested it can be given new input information to predict the output. The typical neural network of a three-layer structure namely: input layer, hidden layer and output layer nodes as shown in Fig. 2. The hidden layer may consist of one or more nonlinear neurons and it performs continuous, nonlinear transformations of the weighted input. Nonlinear activation function transforms a neuron weighted input nonlinearly to an output. In order to determine the capability of the proposed technique to anticipate the voltage stability margin of a power system, a comparative study was conducted by developing an ANN system and used it to perform the similar task by MATLAB software. Many types of neural networks have been designed already, we utilised fully connected neural networks (FCNNs) which are a type of ANN where the architecture is such that all the nodes, or neurons, in one layer are connected to the neurons in the next layer[8].

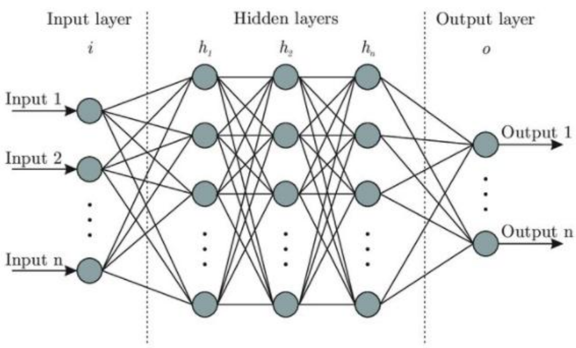

Fig 2: Artificial neural network architecture [9].

4. 30 BUS NETWORK:

In order to evaluate the efficiency of the studied method, IEEE 30 bus network is used, the single-line diagram of which can be seen in the figure opposite. This network has 6 production bins and 21 consumption buses. The network load level at the nominal operating point is 283.4 MW.

4.1. case study 30 bus:

In this example, to investigate the effect of ULTC on system load, we study the IEEE 30-bus network. For this purpose, we
discrete pulses in it. Now by increasing the load of the whole system, we control the voltage of the weakest bus. Thus, whenever the bus voltage is less than 0.95 per unit by increasing the load, by changing the transformer pulse in that bus, we adjust the voltage in the allowable range between 0.95 per unit to 1.05 per unit. In this regard, following finding the maximum load limit of the system, we draw diagrams of the minimum specific value of the Jacobin matrix and the maximum power in terms of voltage. The single-line diagram of the IEEE 30-bus test system is shown in Figure 3.

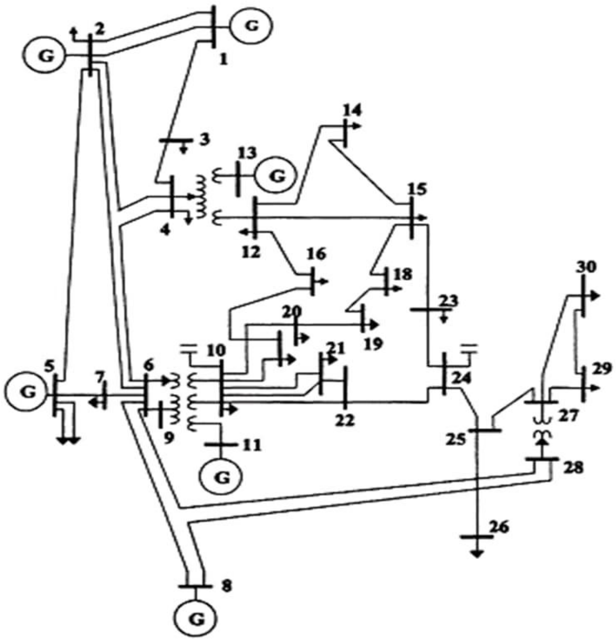

Fig 3: One-line diagram of IEEE 30-bus system [10].

5. VOLTAGE STABILITY MARGIN NEURAL NETWORK EVALUATOR

Voltage stability range is usually expressed by the voltage stability margin index. The voltage stability margin index in the load domain of M is expressed by equation 6.

$$\mathrm{M} = \sum_{k=1}^{n} PLi(\lambda) - \sum_{k=1}^{n} PLi0 = \lambda \sum_{k=1}^{n} KLiPLi \quad (6)$$

6. NEURAL NETWORK MODEL AND LEARNING PARAMETERS

In this paper, a modular multilayer perceptron network with error-diffusion training algorithm was used. Each module of this neural network is of the following specifications and parameters:
1. Each module is a network with one input layer, one middle layer and one output layer, and the number of modules is equal to the number of selected system structures and each module is responsible for learning information about a structure. 2. Each module has one neuron in the output layer and the number of neurons in the input layer is equal to the number of selected inputs. 3. Error Sum of Squares (SSE) is considered as a cost function in which Q is the whole number of patterns according to equation 7.

$$\mathrm{SSE} = \sum_{q} (d^{q} - z^{q})^{2} \quad q=1,2,3,\ldots,Q \quad (7)$$

4. Learning process stops before the SSE increases or when the number of epochs equals 10.

7. Estimation of Power System Voltage Stability Margin

By applying each test module, the trained neural network module related to the structure of the test sample will estimate the voltage stability margin of the power system. To calculate the accuracy of the estimation result, the mean calculation and the maximum absolute value of the estimation error were used. The absolute value of the estimation error, for each sample, is calculated using equation 8 in which the actual value and the estimated value are the results obtained from the power system balance tracking method and the neural network method, respectively.

$$AE = \frac{|Actual\ Value - Estimated\ Vale|}{Actual\ Value} * 100 \qquad (8)$$

8. Results

The MATLAB Neural Network Training tool (nntraintool) was used to perform the training of the ANN. The training was stopped after 9 epochs. We used the information provided by nntraintool to analyse the results obtained with algorithm. Figure 4 shows ANN best training performance, according to the figure, at epoch 9, mse=12.26 which is the lowest error and closest result to best validation.

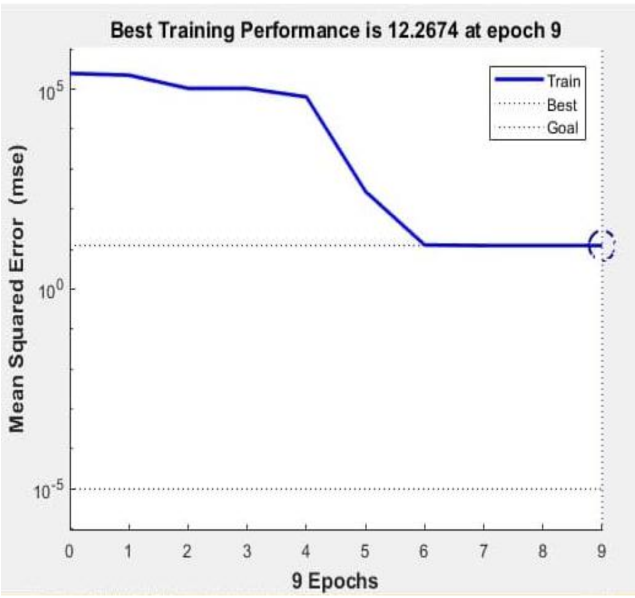

Fig 4: The best validation performance.

Next, Figure 5 shows the evolution of the gradient so as to find the uniformity (the minimum of the cost function) versus the validation check number. In order to terminate the training, the magnitude of the gradient and the number of validation checks were utilized. As the training reaches a minimum of its performance, the gradient will become very small. The validation check number represents the successive iteration number. The maximum performance was found to be at epoch 9 due to the lowest error in Gradient=4.30.

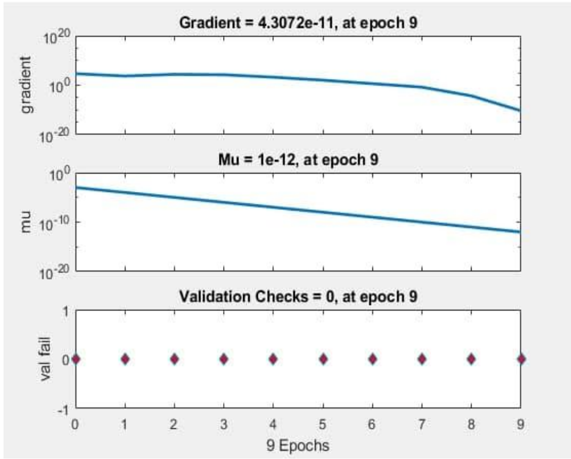

Fig 5: The variation of gradient error and validation checks

Finally, as it may be noticed in Figure 6, there is a regression analysis between the desired purposes and the network response. The value of R indicates the correlation coefficient between outputs and objectives. Here, the R-value is over 0.99 which means the network response is satisfactory.

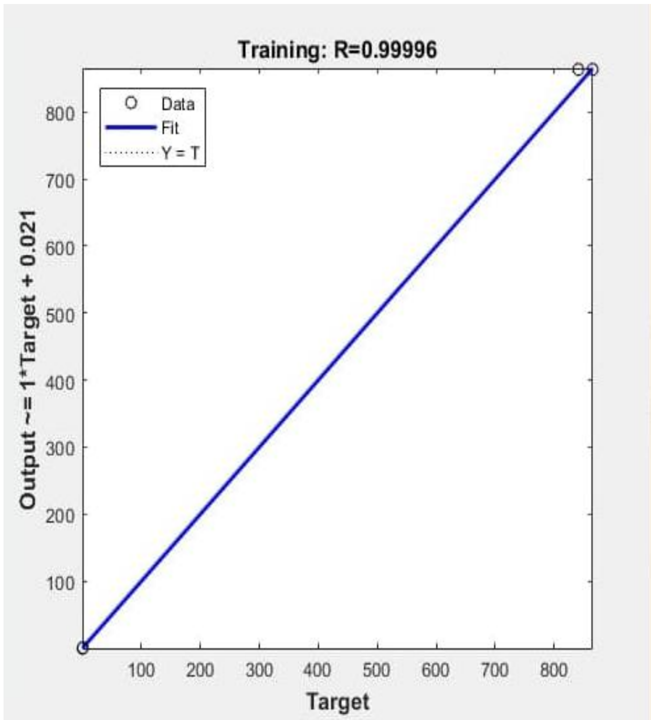

Fig 6: Regression analysis between the network response and the ideal purpose.

Fig 7 indicates that the maximum power which can be loaded in system must be under approximately 863.36MW in which point, if a little load is added, the network faces breakdown voltage.

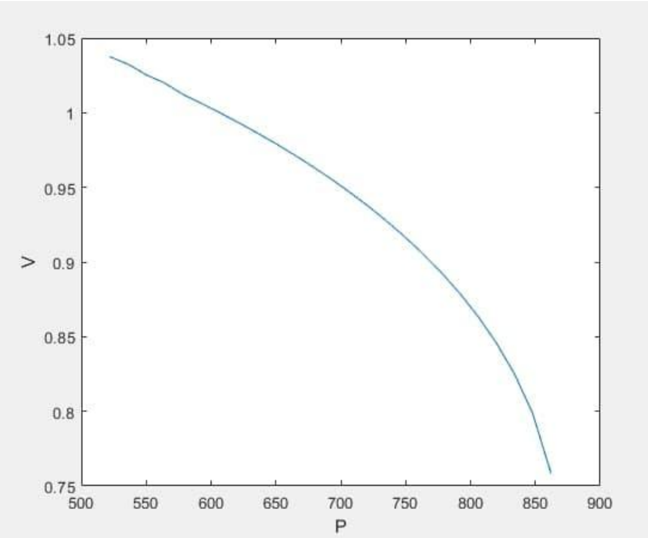

Fig 7: The maximum power for the system

Fig 8 shows the minimum value of Jacobean matrix which was found at epoch 9.

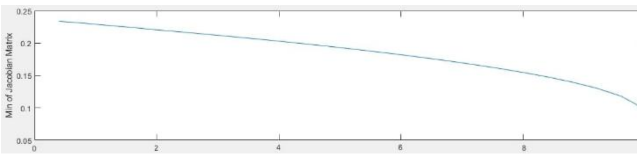

Fig 8: The minimum value of Jacobean matrix

According to the system of formulation and model implementation in the artificial neural network, we set the minimum specified value of the Jacobin matrix to 0.0993 and the critical point of network voltage to 0.7596, and finally the load limit of the system to 863.36 [MW].

9. Conclusion

In this paper, one of the major problems of the power system, namely voltage stability and load limit of the system is examined. Since the load margin and voltage drop are directly related to each other. The problem has been used. Implementing this problem, a large network of 30 buses has been implemented to show its work well.

References

[1] C.W. Taylor “Improving Grid Behavio” *IEEE Spectr*, vol. 36, pp. 40-45, 1999.

[2] M. Klaric, I. Kuzle, and S. TesnjK “Under voltage laod shedding using global voltage collapse”, *IEEE PES Power System Conference and Exposition*, Vol. 1, pp. 453-459, 2004.

[3] D. B. Arnold, M. Sankur, R. Dobbe, K. Brady, D. S. Callaway, and A. V. Meier, "Optimal dispatch of reactive power for voltage regulation and balancing in unbalanced distribution systems," in *2016 Power and Energy Society General Meeting*, 2016, pp. 1-5.

[4] H. D. Chiang, I. Dobson, R.J. Thomas, J.s. Thorp "On voltage collapse in electric power systems" *IEEE Transactions on Power Systems*, vol. 5, no. 2, pp. 601-611, 1990.

[5] Y. A. Mobarak, and M. M. Hussein "Voltage Instability and Voltage Collapse as Influenced by Cold Inrush Current" *ICGST-ACSE Journal*, Vol. 12, no. 1, pp. 9-20, 2012.

[6] M. Begovic (Vice Chair), J. Bright, T. Domin, S. Easterday-McPadden, A. Girgis, W. Hartmann, C. Henville (Chair), M. Ibrahim, K. Kozminski, R. Marttila, G. Michel, K. Mustaphi, D. Novosel, B. Pettigrew, M. Sachdev, H. Shuh, P. Solanics, J. Williams. Voltage Collapse Mitigation, y IEEE Power System Relaying Committee, Rep. Des.1996

[7] A. Ali, A. Eid, and M. Abdel-Akher, "Online Voltage Instability Detection of Distribution Systems for Smart-Grid Applications" *International Journal of Automation and Power Engineering*, vol. 1, pp. 75-80, 2012.

[8] M.V Suganyadevi and C.K. Babulal, "Support Vector Regression Model for the prediction of Loadability Margin of a Power System," *Applied Soft Computing*, vol. 24, pp. 304-315, 2014.

[9] F. Bre, J. M. Gimenez, V. D. Fachinotti, "Prediction ofwind pressure coefficients on building surfaces using artificial neuralnetworks,." *Energy and Buildings*, vol. 158, pp. 1429-1441, 2018.

[10] S. Agatonovic-Kustrin and R. Beresford “Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research.” *Journal of Pharmaceutical and Biomedical Analysis,* vol. 22 no. 2000, pp. 717–727,1999.