Artificial Intelligence based Power Stability Analysis

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***Abstract*: The stability analysis is considered as a crucial problem for a reliable and safe power system. Voltage stability refers to a power system's ability to maintain consistent, acceptable voltages across all of its buses. The measurement of the voltage stability index (VSI) for a power system condition can operate as an accurate and quick indicator of the systems near to voltage instability. The application of intelligent methods based on artificial neural networks (ANN), fuzzy logic, and evolutionary algorithms to the problem of voltage stability assessment has recently piqued interest. With the capacity to provide non-linear input/output mapping, parallel processing, learning, and generalization, ANNs have the potential to be suitable for estimating power system VSIs without solving the governing power system equations. This paper presents the power stability analysis based on ANN and K-nearest neighbor. For each scenario, Power Stability Analysis (PSA) utilizing VSI is performed for several option loading strategies of power network creating ANN models. The outcome was proven to be effective in analyzing voltage stability issues, specifically in ranking network buses in order of vulnerability.**

***Keywords*: power Stability Analysis, Artificial Neural Network, K-Nearest Neighbor, Machine Learning**

1. Introduction

Large-scale power systems control the balance of electricity supply and demand in an ever-changing environment. Such systems' stability is defined by their capacity to recover quickly from perturbations. As demonstrated in Figure 1, security and reliability can be utilised to examine stability holistically. Security, often known as resiliency, is measured by the chance of essential system infrastructure continuing to provide service to clients after a disruption. Due to instability, two systems with comparable stability margins may differ in security. [1] To put it another way, a system that lacks sufficient power cannot be deemed stable. The system's consistency is used to determine its reliability.

Power system stability is defined by the Institute of Electrical and Electronics Engineers (IEEE) and the International Council on Large Electric Systems (CIGRE), with the caveat that the power system architecture must stay mainly intact. [2] This relates to the technique of islanding, which occurs when a large disturbance splits a power system into smaller subsystems. This research does not look into islanding, but rather the collaborative behaviour of components that help with the return to normal operation. Large events and tiny disturbances are two types of disturbances. Large events are abrupt changes in load demand, transmission capability, or generation capacity that cause the power system's general behaviour to become unstable. Variations in power demand, often known as load changes, are the most common source of minor disruptions.

However, some variations in load, such as the demand for electricity during the Super Bowl, can be dramatic. [3] Atypical weather occurrences generally generate large disturbances, which might involve generating loss or transmission line failure. The capacity of a system to return to a steady state operating in the shortest amount of time after experiencing any transience or disruption is referred to as power stability [4-7]. Several synchronous generators are connected to a bus with the same frequency and phase sequence as the generators in power plants. As a result, for a reliable operation, we must synchronies the bus with the generators throughout the full generating and transmission process.

For this reason, the power system stability is also referred to as synchronous stability and is defined as the ability of the system to return to synchronism after having undergone some disturbance due to switching on and off of load or due to line transience [8-9]. The power system stability or synchronous stability of a power system can be of several types depending upon the nature of the disturbance, and for successful analysis, it can be classified into the following three types as shown below:

- Steady state stability.
- Transient stability.
- Dynamic stability.

2. Proposed Methodology

The flow diagram of the proposed system is shown in Figure 1. An Artificial Neural Network (ANN) is a signal processing network that receives, processes, and sends out signals. ANNs go through a learning or training phase at first, which involves modifying the weight co-efficient to fully satisfy the output criteria. 10,11 . Unsupervised and supervised training processes are both available. The desired output is known to the neural network in the supervised training process, and weights are adjusted accordingly, whereas the desired output is unknown to the neural network in the unsupervised training process12. Single Layer Feed Forward Network (SLFF), Multi-Layer Feed Forward Network (MLFF), and Cascade Correlation architecture are all examples of neural network designs (CC). Feed forward networks consist of an input layer, one or more hidden layers, and an output layer. The signal in feed forward networks only goes in one direction. SLFF refers to a network with only one hidden layer, whereas MLFF13 refers to a network with several hidden layers. A neuron in a CC architecture receives system inputs as well as all of the previous levels' outputs. There are various advantages of employing CC over feed forward networks, including a rapid learning process, network size and topology determination, and no error signal back propagation.

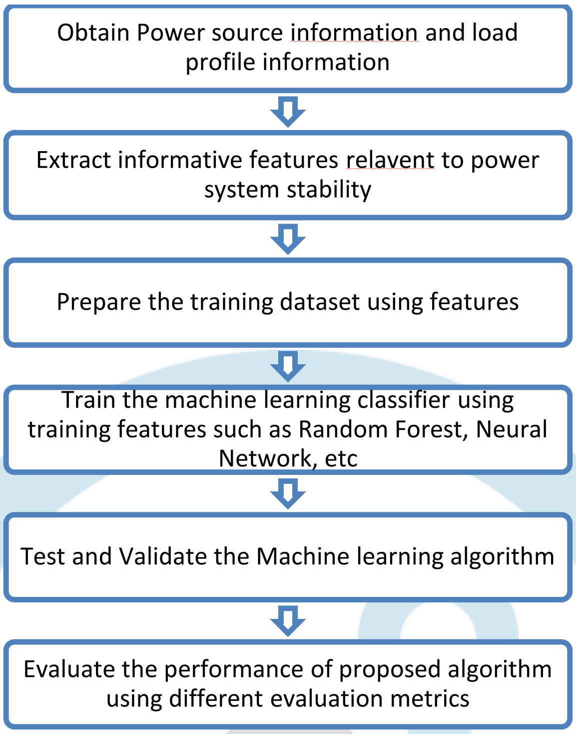

Fig. 1 Flow diagram of proposed system

The proposed model is able to analyze the various effects such as lie to ground faults, line to line faults, etc that degrades the power quality. The ANN uses the training data for the learning of network. The test signal is tested on the trained network to test the faults in electrical bus to analyze the power stability of the system. The figures for the proposed systems flow are shown in Fig. 1 and 2. The detailed process of the application of the machine learning algorithms for the power stability analysis using KNN/ANN is shown in Fig. 2.

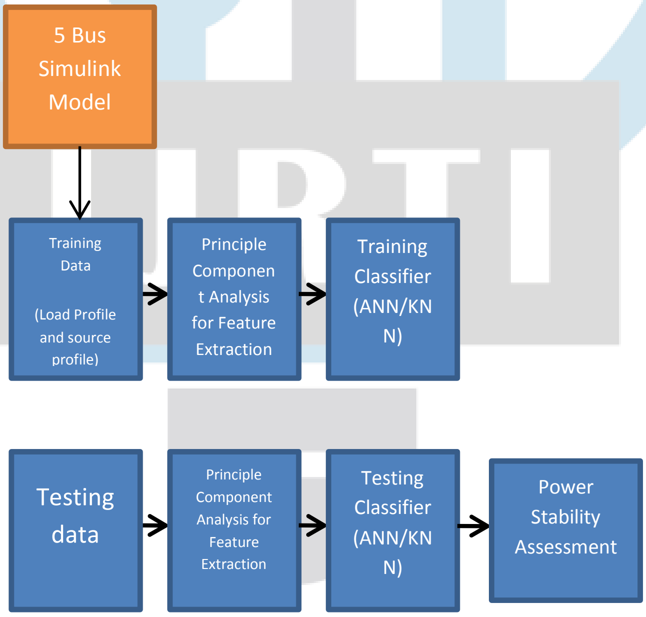

Fig. 2 Machine learning based power stability analysis

The input layer of the FNN accepts the features of supply voltage collected from the feature extraction algorithm. The number of nodes in the input layer is equal to the length of features provided to the network. The hidden layer accepts the output of the input layer as the input and it calculates the weighted sum of the input and bias for every node as given in equation 1. After extensive experimentation we have finalized 10 hidden layers for implementation.

$$\sum_{j=0}^{d} w_{hj} x_j \tag{1}$$

The sigmoid function helps to keep the output of any layer in the bounded form and it is given by equation 2 and 3.

$$\mathrm{sigmoid}(a) = \frac{1}{1 + e^{-a}} \tag{2}$$

$$z_h = \mathrm{sigmoid}\left(\sum_{j=0}^{d} w_{hj}x_j\right) = \frac{1}{1 + e^{-\sum_{j=0}^{d} w_{hj}x_j}} \tag{3}$$

The output layer weights are calculated based on the hidden layer output and bias of the hidden layer (z_h) as given in Eq. 4. Output layer weights are considered for the error calculation.

$$o_i = \sum_{h=0}^{H} v_{ih}z_h \tag{4}$$

3. Experimental results and Discussions

The proposed system is implemented using MATLAB 2018a on personal computer having 4GB RAM and 2.64GHz processing speed on windows environment. The proposed system used 5-bus system for the power stability analysis which is simulated using MATLAB simulink. The MATLAB simulink model or the 5-bus electrical system is shown in Fig. 3.

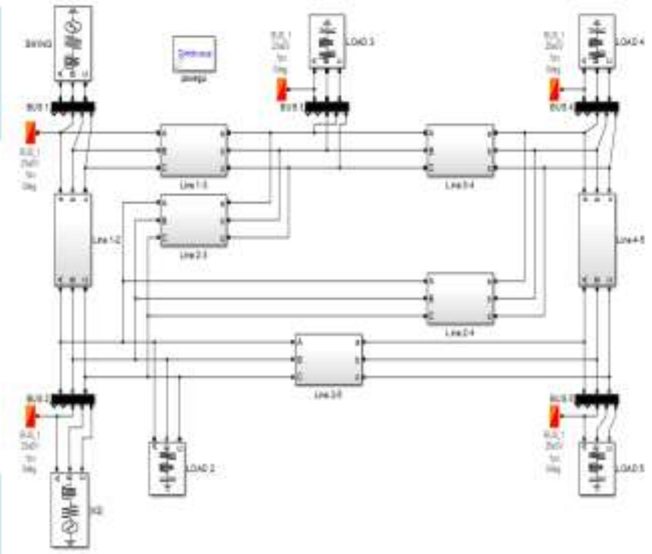

Fig. 3 MATLAB simulink model for 5-bus system

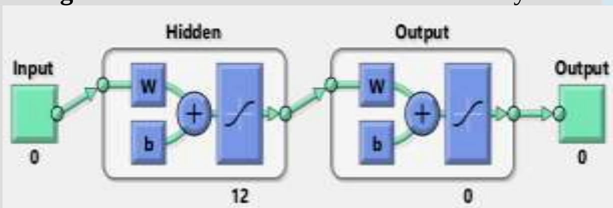

Fig. 4 Neural Network model with 12 hidden layers

Fig. 4 shows neural network model used for voltage stability analysis. The proposed system is able to detect the line faults, line to ground faults and line to line faults in the system using ANN. It provided an accuracy of 90% for the fault detection. The supply voltage and load voltages are given in Fig. 5 and 6.

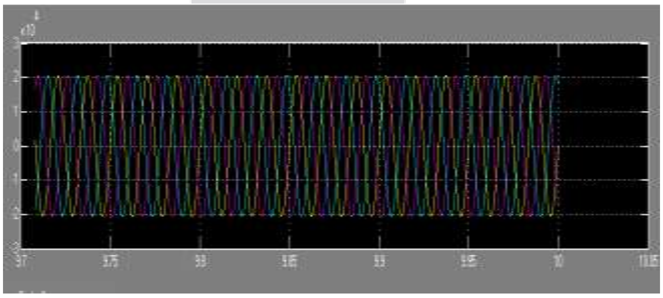

Fig. 5 Supply voltage

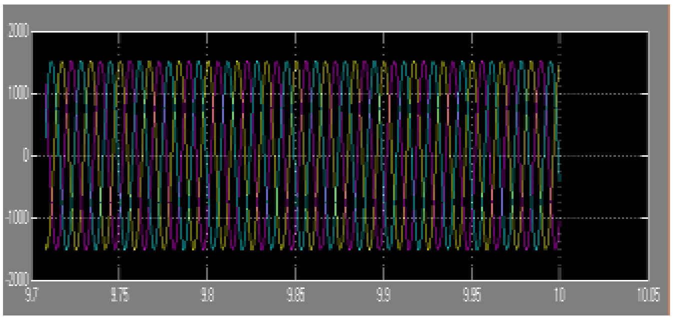

Fig. 6 Load voltage (Load 3)

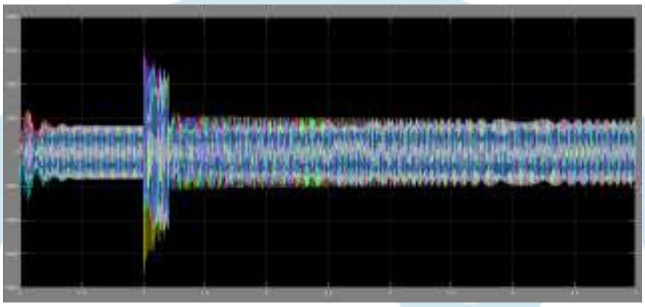

Fig. 7 The change in voltage due to line-line fault (A-B)

The change in voltage due to line-line fault (A-B) is shown in Fig. 7. The steady state voltages and other parameters obtained using ANN are described in Fig. 8.

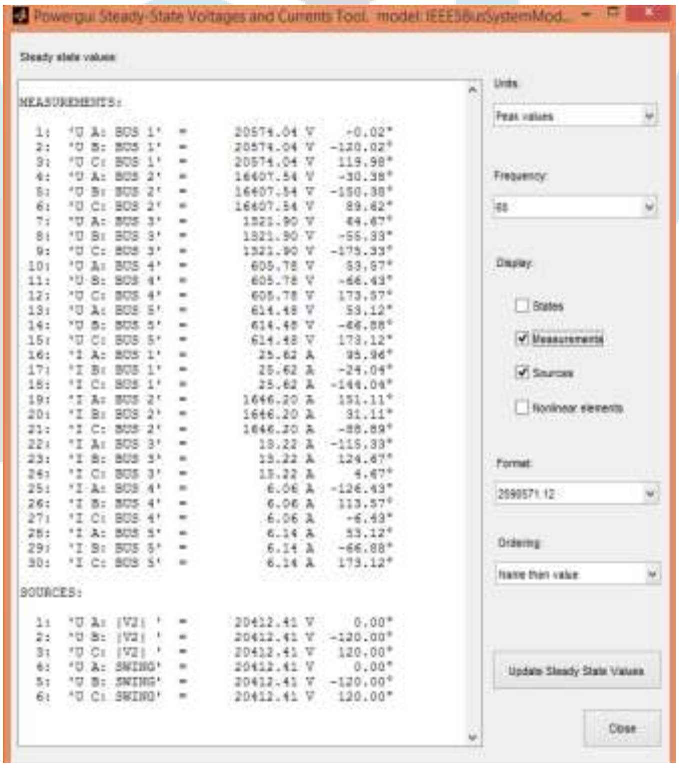

Fig. 8. Steady state voltages of system

Recently deep learning are widely used for many automatic application in 1-D and 2-D signal processing that has shown significant improvement in the supervised learning applications [20-23]. However, deep learning based techniques are rarely applied for electrical system analysis. Hence, in future the concentration can be given on deep learning based power stability analysis.

4. Conclusions and Future Scope

The suggested ANN-based Voltage Stability Assessment and Analysis tool was constructed using ANN and Continuation Power Flow Methods. The suggested ANN-based Voltage Stability Assessment and Analysis tool may be used in a variety of ways, opening up various possibilities for future research. The trained ANN is predicted to be particularly beneficial for real-time monitoring and control of power systems, in addition to using the suggested ANN-based technique for planning. This real-time voltage stability monitoring and assessment tool may be integrated into a contemporary Energy Management System when utilised in this way. In such an application, the current system state and operating conditions can be obtained using the results of the State Estimator and measurements obtained from tools such as SCADA, which can then be converted to variables required to describe the system behaviour, allowing for online generation of input patterns.

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