Online Monitoring of Voltage Stability Margin using Levenberg–Marquardt Algorithm

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***Abstract*—Major blackouts caused by voltage collapse have made the voltage stability problem one of the most significant challenges in the planning and operation of the modern electric power systems. Voltage Instability usually begins with an initial and progressive decrease in voltage magnitude until a sharp abrupt decline occurs. Often these voltage magnitudes lie in the acceptable range with no advance warning of the sudden change. Hence the need for a practical measure of the distance from the current operating state to the voltage collapse point, including the provision for an early warning of the critical situation is necessary. Voltage Stability Margin (VSM) is defined as the distance from the current operation state to the maximum voltage stability limit point according to the system loading parameters. Therefore a new method is designed to approximate the Voltage Stability Margin (VSM) with sufficient accuracy and high execution using efficient feature selection method of ANN which possibly employ a single ANN for estimating the VSM for several system configurations. The proposed online voltage stability monitoring scheme is applied to the IEEE 39-bus test system and is simulated using the MATLAB based free and open source software tool PSAT (Power System Analysis Toolbox) to obtain the required target pattern/output. However, the proposed Neural Network model is implemented using the software MATLAB [1].**

Keywords—Voltage Stability Margin;Continuation Power Flow; feature selection; Artificial Neural Network;

I. INTRODUCTION

Voltage Stability has been an area of concern and interest over the past years due to increased demand and instability issues. Prevailing techniques for voltage stability analysis are static methods and dynamic methods. The static procedures are based on the steady state power flow model of the power systems and such simplified ways usually lead to unreliable results. For better real-time scenario considering the system dynamics into account would help but they might be time consuming [2].

Using Artificial Neural Networks (ANN) would be a better alternative to overcome the above mentioned problems. ANNs have the ability to learn complex non linear relationships and their modular structures which allow parallel processing. They are basically information processing systems which process data replicating the biological neural systems. Application of neural networks to power system problems has been an area of interest off late [3]. The prevailing methods proposed in the past for online voltage stability monitoring using ANNs have led to acceptable results in which the majority of the published works are in the literature based on the multi-layered perceptron (MLP) neural networks while the other methods rely on the Radial Basis Function (RBF) networks [4].

A Multilayer Perceptron (MLP) is a feed-forward artificial neural network model that maps sets of input data onto a set of suitable outputs. A multilayer perceptron consists of directed graph with multiple layers of nodes with each layer fully connected to the next one.

II. EXISTING SCENARIO

Existing ANN based designs need to train a new neural network for every change in the power system topology (configuration) leading to increased size and cost of the ANN [1]. In a real-time scenario, a large power system may encounter a huge number of potentially credible contingencies and training a separate ANN for each resulting configuration would be a demanding and tedious task.

III. VOLTAGE STABILITY MARGIN

Voltage Instability is usually caused when the system loads attempt to draw excess power than what could be delivered by the Transmission and Distribution System [5]. The Voltage Stability Margin (VSM) is defined as the distance from the current operation state to the maximum voltage stability limit point (voltage collapse point) according to the system loading parameter. As the system loading goes up the solution of this margin coalesce at a critical point called Saddle Nose Point (SNB).The variation of system voltage profile is as shown in Fig.1.

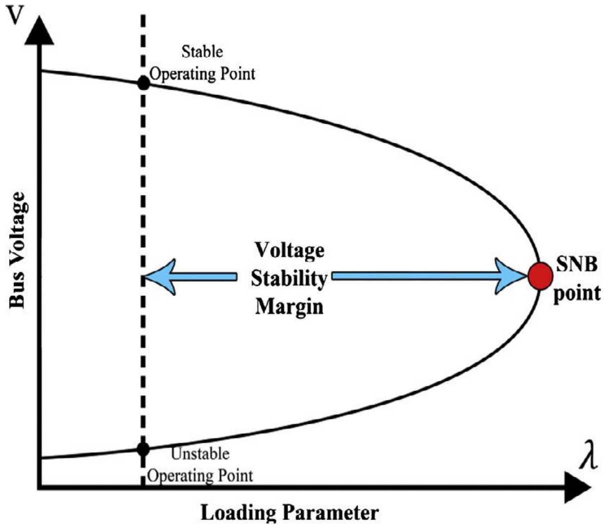

Fig. 1. Voltage Stability Margin Plot

For the calculation of the Voltage Stability Margin (VSM), the SNB (Saddle Node Bifurcation or Nose Point) [6] point should be located along the curve in the *Fig.1*.

The SNB point is usually identified using the continuation methods. Initially starting at a point they trace the equilibrium points of the power system as the loading parameter changes for various system conditions. Regardless of the Continuation methods being accurate and robust they are expensive computationally for large power systems [7]. From Fig.1.it is evident that SNB or Nose point corresponds to the maximum loading point of the bus which is λ_{max}. It can thus be stated that Voltage Stability Margin is equal to λ_{max}. . Therefore the Voltage Stability Margin computed by continuation process can be used as the Target output for training patterns.

In practice, a power system may be subjected to a wide range of contingencies like unexpected line outages etc. during its actual operating conditions [8]. When a contingency occurs, the system configuration may change and thereby leading to the failure of the trained ANN to provide an accurate computation of the VSM as the input–output relationship could not be captured properly.

IV. ARTIFICIAL NEURAL NETWORK

Artificial Neural Networks can be used as an attractive alternative to overcome the above problem of the continuation method. Artificial neural network (ANN) based methods have off late been the most popular methods proposed for different problems of power system as they can easily, accurately and rapidly synthesize complex mappings [9]. As mentioned, the Multi-Layered Perceptron (MLP) network is used in this work which consists of an input layer, an output layer and a single or multiple hidden layers. MLP model can be trained 10–100 times faster by applying high performance algorithms. In this paper, Levenberg–Marquardt Algorithm is used to train the MLP network which is considered to be one of the fastest training algorithms [10].

V. METHODOLOGY

Suitable set of input variables are chosen for prediction of the VSM.

- *PV buses*: voltage magnitudes and generated active powers.
- *All the System Loads*: active and reactive powers.
- *All the System Generators*: generated reactive powers.
- *Slack Bus*: generated active power.

For generation of training and/or testing patterns all the above mentioned input variables are varied within a specified range randomly. The voltage magnitudes of all the PV buses are varied between 0.9 and 1.1 times their base values. For all the system buses Real and Reactive loads vary between 0.7 to 1.2 times their base values as given in the below set of equations

$$V_{PVi0}(k) = V_{PVib}(0.9+0.2\mathcal{E}^{i}{}_{VPV}(k))$$
$$P_{Li0}(k) = P_{Lib}(0.7+0.5\mathcal{E}^{i}{}_{PL}(k))$$
$$Q_{Li0}(k) = Q_{Lib}(0.7+0.5\mathcal{E}^{i}{}_{QL}(k))$$

where $P_{Li0}(k)$, $Q_{Li0}(k)$ and $V_{PVi0}(k)$ are the load active power, load reactive power and the PV bus voltage magnitude at the ith bus for the kth training pattern. Similarly, P_{Lib}, Q_{Lib} and V_{PVib} are the ith bus base load active power, base load reactive power and the PV bus voltage magnitude. $\mathcal{E}$ is a uniformly varied random number between 0 and 1. Each randomly generated set of operating conditions are then subjected to the Newton-Raphson power flow program to ensure a feasible steady state operating requirements and the deviating cases are neglected.

In this paper, IEEE 39-bus system is used for the analysis. For the verified operating points from above, the system initially is subjected to continuation power flow method using PSAT [11] to compute the Voltage Stability Margin. This calculated VSM is used as the target output for the training and testing patterns of ANN.

During the normal operating conditions a power system may be subjected to various contingencies and hence we need to train the system to estimate the VSM for various system topologies. For the selected system the most possible contingencies are chosen specifically analyzing the single line outages and finally a single neural network is trained to estimate VSM for all the selected contingencies along with the base case.

VI. THE SIMULATION RESULTS

The IEEE 39-bus system is used to demonstrate the proposed method for online voltage stability margin analysis. The SLD (Single Line Diagram) of the 39-bus test system is as shown in *Fig.2*. The IEEE 39-bus test case has 29 PQ buses, 46 lines, 10 synchronous machines, 9 PV buses and 19 system loads. Bus 1 was taken as Slack bus and its voltage magnitude and angle were assumed to be fixed.

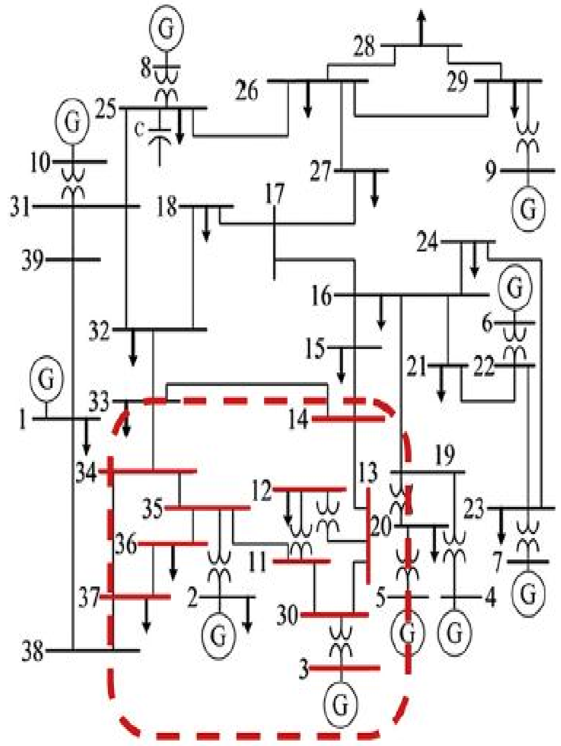

Fig.2. IEEE 39-bus System

The software tool PSAT is used to find the VSM using Continuation Power Flow (CPF) for the base case operating conditions and for a selected number of the worst case contingencies. Here we consider the contingencies for the outages of line between bus 15 - 16, bus 32 - 33, bus 37 - 38, bus 21 - 22 and bus 31 - 32. *Fig.3.* shows the complete base case PV curve for bus 11 obtained on executing CPF using PSAT. Similarly CPF is executed for all the mentioned cases.

Using the procedure in section *V*, 58 random patterns were generated for the 6 test cases of which 75% were chosen as training patterns and 25% as testing patterns. Therefore 264 (44*6) training patterns and 84 (14*6) testing patterns were collected.

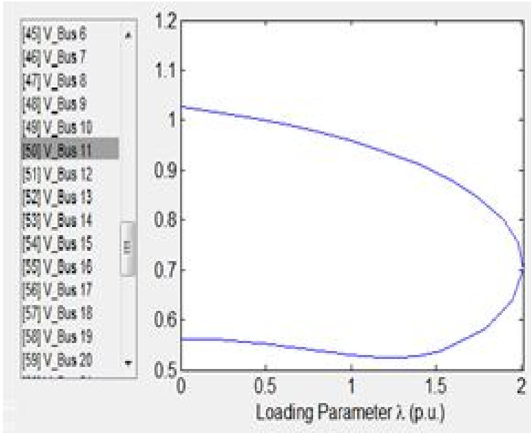

Fig .3. Continuation Power Flow Based Plot for voltage bus 11

A proper structure is chosen for the neural network with appropriate activation function for its neurons. An MLP neural network consisting 1 input layer, 1 hidden layer with 10 neurons and one output layer was used the proposed MLP-ANN was trained using Levenberg-Marquardt algorithm as shown in *Fig.4.*

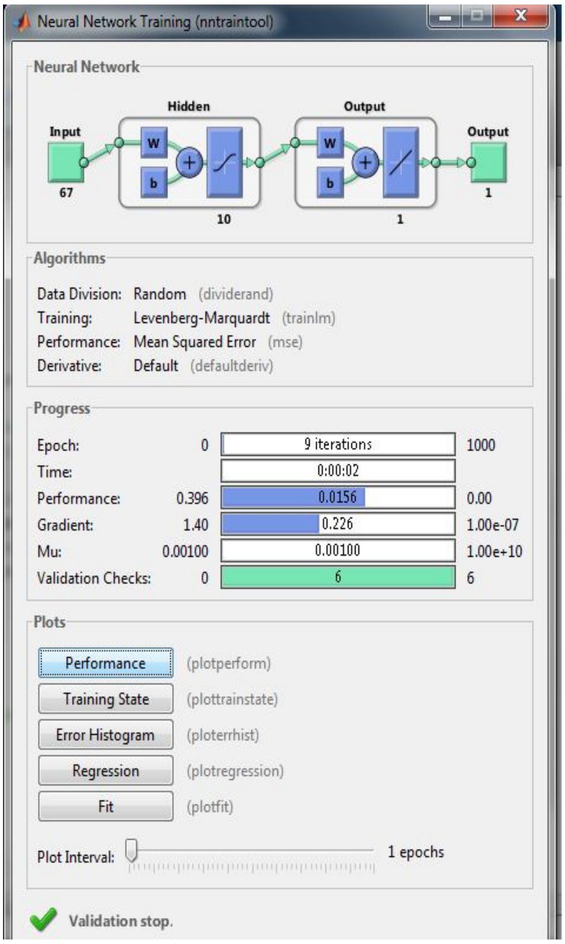

Fig.4. Artificial Neural Network Training using Levenberg- Marquardt Algorithm

The comparison between the estimated VSM using ANN and the actual VSM using CPF are shown in *Fig.5*.The proposed MLP ANN was able to reach its target within a very small time duration which could be less than 2 second while CPF procedure took more than 4 seconds. It can be seen that the accuracy of estimation between the two is reasonably good from the comparison.

Also to state that the Continuation Power Flow (CPF) execution required different input file for each of the tested system configuration while ANN could include all the inputs for the entire configuration in a single file in the form of matrices. This proves to be lesser time consuming effort with the same accuracy. Additionally PSAT accepts input files in the specified format to execute the CPF which adds on to the time consumption.

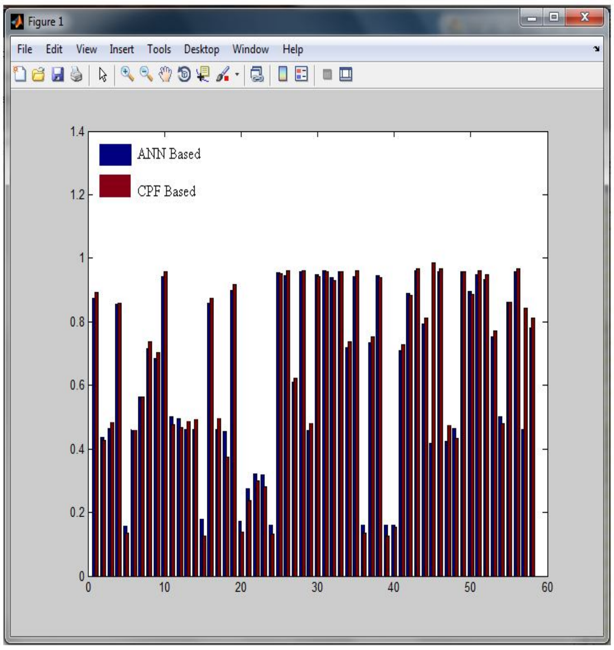

Fig.4. Comparison of ANN estimated VSM and the corresponding actual VSM from CPF for different configurations of the IEEE 39-bus system.

VII. CONCLUSION

Voltage stability problem is a major cause of concern for the power system planners and operators off late due to the increased black-outs. For online applications, potentially dangerous situations leading to voltage collapse must be recognized by the system operators for quick remedial actions. Thus, online voltage stability monitoring is becoming an inevitable part of the energy management systems (EMS). To help out of these problems, here an artificial neural network (ANN)-based approach is presented for online estimation of a voltage stability margin (VSM). Compared to most previously published works employing a separate ANN for different contingences this scheme uses an online estimation of the VSM for several system configurations by only one ANN. Results were obtained on the IEEE 39-bus system. The results obtained confirmed that using ANN approach has some obvious benefits in terms of the computational requirements and future data collection, along with improved accuracy.

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