Analysis of Voltage Stability Margin and Prediction of Asynchronous Machine using ANN

Naresh Kumar[1], Minakshi Hooda[2], Sunil Kumar[3]

[1]Murthal University, Sonipat, Haryana, India
mahakhooda325@gmail.com

[2]Department of Electronics Engineering, YMCA UST, Faridabad, India
skmee207@gmail.com

Abstract: ***This paper presents an ANN based model for predicting stability margin for an asynchronous machine power system prone to voltage instability. Such a model may be employed either for direct prediction of the stability margin based on the existing loading conditions or for forecasting the loading conditions for a future time period and then providing an estimate of the stability margin. The neural networks employed are the multi layer perceptron (MLP) with a second order learning rule and the radial basis function (RBF) network and feed forward neural network. The simulation results for a sample 5-bus system indicate that the ANN models provide a fairly accurate and fast prediction of the stability margin making them, suitable for application in an on-line energy management system.***

Keywords: ANN, voltage instability, loading conditions, stability margin, radial basis function

1. Introduction

During the last couple of decades, the complexity of transmission systems has increased. There are an increasing amount of interconnections in power systems, and at the same time they are being operated closer to their capability limits, due to economic and environmental considerations. As a result of this there have been many power disruptions [9, 36]; typically these are characterized by a progressive fall of voltages and shortage of reactive power supply. As opposed to the much studied angular stability, this is an event that can take place over a long period of time from minutes to hours. Eventually it can lead to voltages going under acceptable levels, tripping of different equipment and islanding of the system or total blackout. The phenomenon characterizing these catastrophic events is often referred to as a voltage collapse and a comprehensive body of literature exists on this subject.

Voltage stability has been of the keen interest of industry and research sectors around the world since the power system is being operated closer to the limit whereas the network expansion is restricted due to many reasons such as lack of investment or serious concerns on environmental problems. There are several works previously proposed to predict the voltage stability and proximity to voltage collapse based on conventional approach, for example PV and QV curves, sensitivity based indices [1] and continuation methods [2]. Other methods, such as bifurcation theory [3], energy function [4] singular value decomposition [5], etc have been also reported in the literature. These methods provide complete and accurate results but they are usually hampered by the fact that they consume long computing time because of the requirement for repetitive power flow calculations.

Online voltage security assessment is a very useful but not yet becomes a widely used tool that measures the distance from the current operating condition at any time to the critical point. Artificial neural network have recently received widespread attention from researchers for this application. Most of ANN applications have been implemented using multi-layered feed-forward neural networks trained by back propagation because of their robustness to input and system noise, their capability of handling incomplete or corrupt input data. However, in typical power systems there are voluminous amount of input data. Then, the success of ANN applications also depends on the systematic approach of selecting highly important features which will result in a compact and efficient ANN. Different feature reduction methods are compared in this paper. This paper is organized as follows. The method of real-time tracking of Thevenin equivalent and brief summary of considered indices are presented in Section II. Section III presents the design of the proposed method. Simulation results are given in section IV and section V concludes the paper and suggests the future work.

Synchronous machines are used in many fields, as in motor applications or in generator applications. The goals to have a synchronous machine model can be split into two groups: (1) to achieve further insight in the complex electro-magnetic behavior of the machine [1, 2] and (2) for simulation or control purposes [3].

This paper presents an ANN based model for voltage stability margin prediction. Section II presents derivation of a voltage stability proximity indicator based on an energy function that reflects the system loading conditions. Section III describes an algorithm to calculate low-voltage load-flow solutions necessary to determine the energy margin. Section IV presents the ANN based model for margin prediction. The margin may be predicted using existing loading conditions on a network or loading conditions that have been forecasted by a different ANN. Section V presents the results obtained by applying the ANN based models to an sample 5-bus system and section VI gives the main conclusions.

2. Energy Margin as a Proximity Indicator to Voltage Instability

In this section the energy function based voltage stability indicator is discussed. The expression of energy margin as a function of the system state is derived first for a simple radial system. This expression is generalized for an n bus system Consider a two-bus system shown in Fig. 1 with a single series transmission line connecting Buses 1 and 2. Bus 1 is assumed to be a slack bus with voltage magnitude fixed at 1.0 p.u., while a constant P-Q type of load is delivered at Bus 2. The governing algebraic equations for the real and reactive power flows on the line are given as

$f(\alpha,v) = P_L + B_{12} V \sin\alpha = 0$ (1)

$g(\alpha,v) = Q_L - B_{22}V^2 - B_{12} V \cos\alpha = 0$ (2)

where V= voltage magnitude at Bus 2 and $\alpha = \delta_2 - \delta_1$ is the phase angle difference from Bus 2 to Bus 1. Multiplying both sides of (2) by V–l we get,

$g(\alpha, V) = \frac{Q_L}{V} - B_{22}V - B_{12}\cos\alpha = 0$ (3)

The energy based stability margin to indicate vulnerability to voltage instability is obtained by integrating the

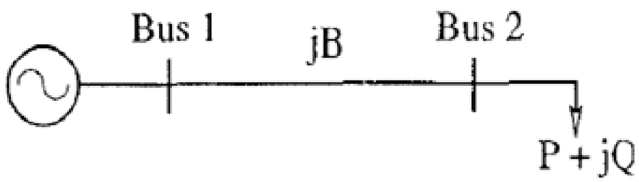


Figure 1: Sample two bus system

3. Mathematical Modeling of Asynchronous Machine

No-Load Test

The no-load test, like the open circuit test on a transformer, gives information about exciting current and rotational losses. The test is performed by applying balanced rated voltage on the stator windings at the rated frequency. The small power provided to the machine is due to core losses, friction and winding loses. Machine will rotate at almost a synchronous speed, which makes slip nearly zero. This test is represented with an equivalent circuit in Figure shown.

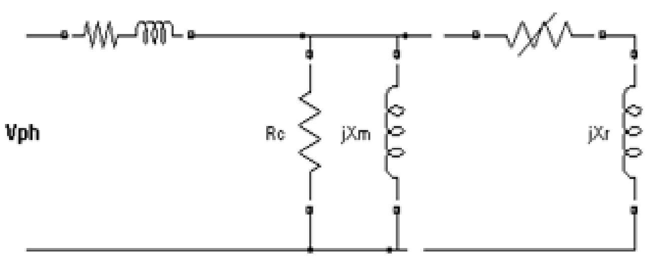


Figure 2: Equivalent Circuit

Values measured during this test are current and its angle with respect to Known voltage. From this we can calculate total power supplied to the machine.

$$\cos(\varphi_o) = \frac{P_{ph}}{V_{ph} I_o}$$

$$I_m = I_o \sin(\varphi_o)$$

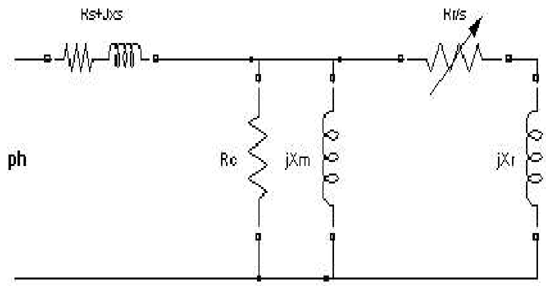
$$I_c = I_o \cos(\varphi_o)$$

$$L_m = \frac{V_{ph}}{2\pi f_s I_m}$$

$$R_c = \frac{V_{ph}}{I_c}$$

Locked Rotor Test

The locked rotor test, like short circuit test on a transformer, provides the information about leakage impedances and rotor resistance. Rotor is at the stand still, while low voltage is applied to stator windings to circulate rated current. Measure the voltage and power to the phase. Since there is no rotation slip, s=1 which gives us following equivalent circuit below



$$\cos(\phi_{sc}) = \frac{P_{ph}}{V_{ph} I_{sc}}$$

$$Z_{sc} = \frac{V_{ph}}{I_{sc}}$$

$$R_r = Z_{sc}\cos(\phi_{sc}) - R_s$$

$$X_{eq} = Z_{sc}\sin(\phi_{sc})$$

$$X_{eq} = X_{ls} + X_{lr}$$

In electrical engineering, direct–quadrature–zero (or dq0) transformation or zero–direct–quadrature (or 0dq) transformation is a mathematical transformation used to simplify the analysis of three-phase circuits. In the case of balanced three-phase circuits, application of the dqo transform reduces the three AC quantities to two DC quantities. Simplified calculations can then be carried out on these imaginary DC quantities before performing the inverse transform to recover the actual three-phase AC results. It is often used in order to simplify the analysis of three phase synchronous machines or to simplify calculations for the control of three-phase inverters. The dqo transform presented here is exceedingly similar to the transform first proposed in 1929 by R.H. Park. In fact, the dqo transform is often referred to as Park's transformation. The dqo transform applied to three-phase currents is shown in matrix form:

$$I_{dqo} = TI_{abc} = \sqrt{\frac{2}{3}} \begin{bmatrix} \cos(\theta) & \cos(\theta - \frac{2\pi}{3}) & \cos(\theta + \frac{2\pi}{3}) \\ \sin(\theta) & \sin(\theta - \frac{2\pi}{3}) & \sin(\theta + \frac{2\pi}{3}) \\ \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2} \end{bmatrix} \begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix}$$

The inverse transform is:

$$I_{abc} = T^{-1} I_{dqo} = \sqrt{\frac{2}{3}} \begin{bmatrix} \cos(\theta) & \sin(\theta) & \frac{\sqrt{2}}{2} \\ \cos(\theta - \frac{2\pi}{3}) & \sin(\theta - \frac{2\pi}{3}) & \frac{\sqrt{2}}{2} \\ \cos(\theta + \frac{2\pi}{3}) & \sin(\theta + \frac{2\pi}{3}) & \frac{\sqrt{2}}{2} \end{bmatrix} \begin{bmatrix} I_d \\ I_q \\ I_o \end{bmatrix}$$

4. ANN based Model for Voltage Stability Margin Prediction

The proposed ANN based model for the determination of the energy margin is shown in Figure. The input to the neural network consists of real and reactive power injections at all load buses in the system for a particular loading condition. The output of the network is the energy margin. For implementing this model the Multi Layer Perceptron (MLP) structure with a second-order learning rule and the Radial Basis Network (RBF) were used. The network was trained with different, sets of loading conditions and energy margins. The range of energy margins should cover the entire range of its variation. After training the network will be able to determine the energy margin which serves as an indicator of the systems proximity to the voltage instability boundary. The complete block diagram for the ANN based voltage stability margin predictor is given in Figure. It contains the ANN models for load forecasting at each node utilizing the load history of the previous hT time period and that for the energy margin determination described above. The load power factor at each node ($Pf_1 \ldots Pf_n$) is assumed to remain constant.

5. Simulation Block

The effectiveness of the energy based voltage stability margin and the proposed ANN model was studied using the Stagg and E1-Abiad five bus system given in the appendix. The results are given below. The proposed ANN based model for the determination of the energy margin is shown in Figure. The input to the neural network the dqo transform presented here is exceedingly similar to the transform first proposed in 1929 by R.H. Park. In fact, the dqo transform is often referred to as Park's transformation. the prediction margin is also define as a reactive power The above figure is showing the response of voltage stability prediction margin, here the stability prediction is 0.6, 0.8 and 1.2 at this value we can control the voltage in terms of Reactive power and Current and voltage, the rotor speed is also define the voltage prediction stability at the rate voltage 1500 rpm.

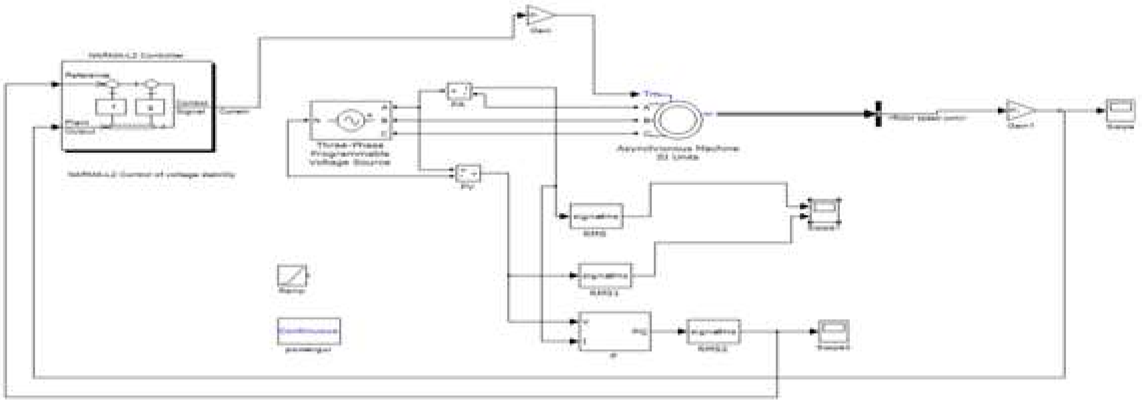


Figure 3: Simulink Block diagram of Asynchronous machine with ANN (NARMA-L2)

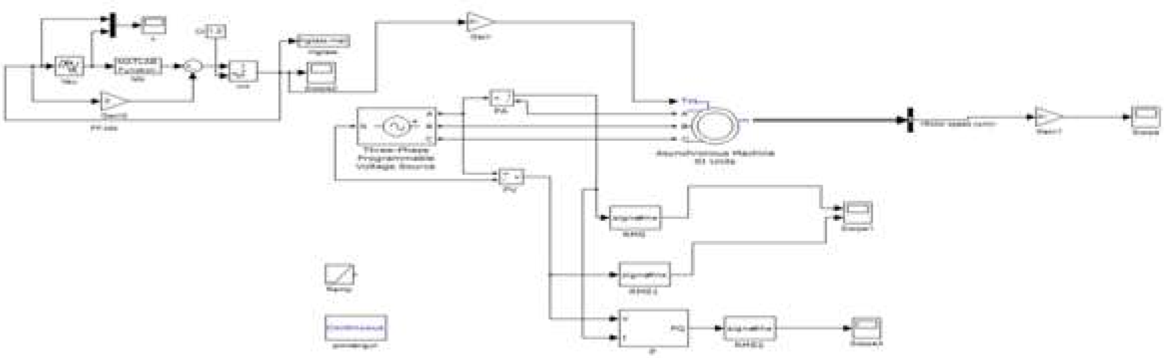


Figure 4: Simulink Block diagram of Asynchronous machine with feed forward Neural Network

6. Result and Explanation

In this section, attributes selected from different methods have been compiled and analyzed. The entire space of attributes consists of real and reactive power injections and voltage and angles at all buses. Only voltage and angles are considered for further processing. This is because voltages and angles are readily available from the phasor measurements. Interestingly, it was observed that using voltage and angles gave better results compared to real and reactive power injections. The consideration of available reactive reserves in computation of voltage stability margin has proven to be very accurate and reliable compared to the Thévenin Equivalent method. The error rate as we approach the loadability limit falls exponentially. The reactive limits of generation or contingencies such as outage of a line influence the reactive loss of a line; however the effect is more benign as compared to Thévenin equivalent. An index calculated from this method would therefore be more reliable. All the computations are based on online measurements. In this paper we defined the voltage stability in terms Reactive Power and RMS Current and voltage.

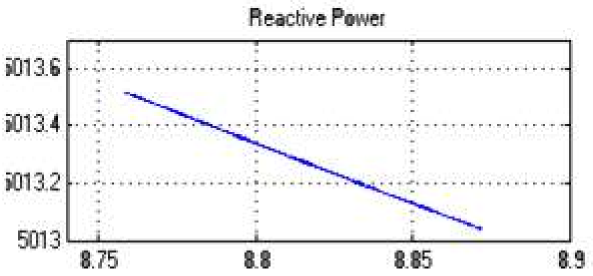


Figure 5: Response of reactive power which not control

The above figure is showing the response of Voltage is not stable and not control in terms of reactive power, so for controlling the voltage of a system we need a controller as Neural Network, after using ANN the response as follow.

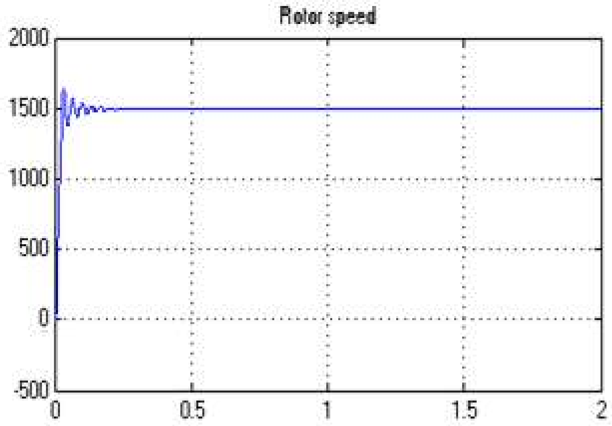


Figure 6: Response of rotor speed at 1500

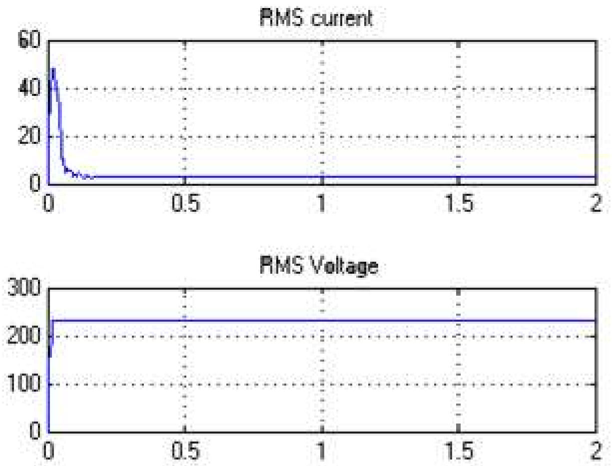


Figure 7: Response of RMS Current and voltage

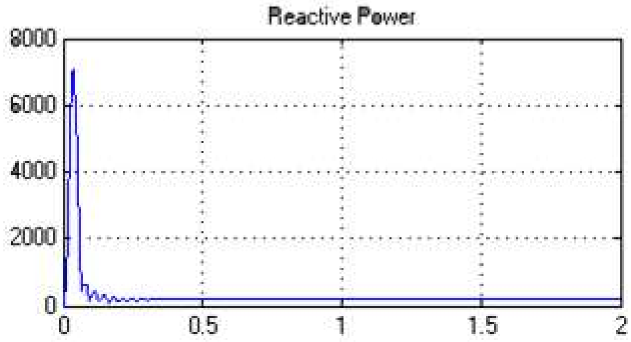


Figure 8: Response of Reactive power control at 0.3 s

The above figure is showing the response of voltage stability prediction margin, here the stability prediction is 0.6, 0.8 and 1.2 at this value we can control the voltage in terms of Reactive power and Current and voltage , the rotor speed is also define the voltage prediction stability at the rate voltage 1500 rpm.

7. Conclusion

This paper gives a synopsis of online voltage stability monitoring. Current practices in online monitoring have been presented along with their drawbacks. The current approach to the problem consists of application of online measurements and stored data. For the first method, use of Thévenin equivalent is prevalent. The equivalent is highly influenced by reactive reserves (generators) hitting their limits. This is also the case for other indices proposed in the literature. Among the data mining methods, DTs are gaining popularity due to their speed, accuracy and system information they provide. In the power system literature, it was found that the work was lacking in a systematic study of attribute selection using power system techniques.

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