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ANN and ANFIS based L-index for Voltage Stability Assessment in Power Systems

Dharshini C.S.[1], Smitha S.S.[2]

[1]*PG Student, M.E. Power Electronics and Drives, Ponjesly College of Engineering*

[2]*Assistant Professor, Department of EEE, Ponjesly College of Engineering*

Abstract — The complexity in power system increases as they grow in their size and interconnections. Rising costs due to inflation and increased environmental concerns has made transmission, as well as generation systems to be operated closer to design limits. Hence Power System Voltage Stability and Voltage Control are emerging as major problems in the day-to-day operation of stressed power systems. In this paper, a Voltage Stability Index (L-Index) is used to assess the voltage stability in Power Systems. The value of L – Index ranges between 0 (no-load condition) and 1 (voltage collapse). Furthermore, Artificial Intelligence has been emerging as a tool for solving Power System problems due to its efficiency in handling nonlinear problems. This project work also applies Artificial Intelligence Techniques such as Artificial Neural Network (ANN) and Adaptive Network Fuzzy Inference System (ANFIS) for the estimation of L – Index in various load buses of Power Systems. Input-output relation of real/reactive power and voltage vectors for generator as well as load buses with the voltage stability Index-L is used as the training dataset for ANN and ANFIS. The proposed approach is tested in standard IEEE 30 bus test system and the results are analysed.

Index Terms— Voltage Stability, Artificial Neural Network(ANN), ANFIS, L-index.

I. INTRODUCTION

Voltage stability has become a major concern in planning and operations of power systems because of its complexity of interconnections. It is well known that voltage instability and collapse have led to major system failures; with the development of power markets, more and more electric utilities are facing voltage stability-imposed limits. Voltage stability is closely associated with power system steady state and dynamic performance. The problem of voltage stability may be simply explained as inability of the power system to provide the reactive power or the egregious consumption of the reactive power by the system itself.

Voltage stability in Power Systems is attracted by researchers in recent years due to the impact of metrological factors. X. Zhang et al. (2023) proposed a load dynamic stability index applicable for short term voltage stability that is closely related to load dynamics. The index further enhanced by incorporating a modification based on the support vector machine method, a data-driven method to improve its properties. X. Jia et al. (2022) considered metrological and geographic information around the transmission lines and proposed a static voltage stability assessment approach based on unified power flow model which was tested in IEEE 14 bus test system with analysis under different operating scenarios. Y. Li et al. (2021) proposed a static voltage stability index that models system intrinsic characteristics rather than represent the system as an infinite bus to investigate the voltage collapse condition. The authors also proposed a tuning algorithm that reveals the inherent relationship between droop coefficients of inverter-based generator and static voltage stability. C. Liu et al. (2020) proposed a measurement-based voltage stability assessment method considering reactive power limits of generators. A relationship is derived between the variation of the generated electromotive force and the load that can be identified and tracked in real time. There are also many conventional approaches proposed for voltage stability assessment based on different indices.

Though different indices and approaches were proposed for static voltage stability assessment, the L-index proposed by P.Kessel and H.Glavitsch (1986) is found to be more effective compared to other indices in terms of static voltage stability enhancement. The indicator-L that varies between 0 and 1 is used for detection of voltage instabilities in a power system. A method for identifying critical buses in a network is proposed based on this index. The advantage of the method lies in the simplicity of the numerical calculation and the expressiveness of the result. M. Salah et al. (2023) tested L-index for its reliability in accurate assessment of the maximum power transfer margin and proposed enhancements considering the results obtained from IEEE 30 bus test case.

This work presented in this paper utilizes the traditional L-index for static stability assessment of a power system. The work also applies Artificial neural network (ANN) and Adaptive network based Fuzzy Inference System (ANFIS) for prediction of L-index of different load buses under different loading conditions. The proposed approach is tested in a standard IEEE 30 bus test case and the results are analyzed.

II. PROPOSED METHODOLOGY

In this paper a static stability index, known as L-index is used for voltage stability assessment. The value of this L-index varies from 0 to 1 and the node which has highest value of L-index is considered as the weakest node in the power system network. Voltage instability occurs in the system when the indicator reaches the value of 1. This index gives a sufficiently accurate and more practical means of the assessment and can express the stability analysis in a simple way.

A. Mathematical Formulation of L-index

The L-index is first calculated for a 2-bus system and then is generalized for multi-bus system.
By applying fundamental principles for a two bus system, we get the result at the time of voltage collapse.

$$|1 + (V0 / V1)| = 1 \qquad (1)$$

This relation is used to define the indicator L for the assessment of voltage stability. It is given by,

$$L = \left|1 + \left(\frac{V_0}{V_1}\right)\right| = \frac{S_1}{Y_{11}V_1^2} \qquad (2)$$

The range of this L-index is given as,

$$\text{R} = \{L / 0 \le L \le 1\} \qquad (3)$$

To assess the stability of a multi bus system, the indicator L has to be extended for the multimode system. As per the basic theory of the multi-bus power system, all the buses can be divided into two categories: Generator bus (PV bus and Slack bus) and Load bus (PQ bus). Because the voltage stability problem is reactive power relative problem, and the generator bus can provide the reactive power to support the voltage magnitude of the bus, it is absolutely necessary that the all of buses be distinguished.

The global indicator L, describing the stability of the complete system is given by,

$$L = \max\left(L_j\right), j \in \alpha_L \qquad (4)$$

$$L = \max\left|1 - \sum_{i\in\alpha_G} F_{ji}\frac{V_i}{V_j}\right|, j \in \alpha_L \qquad (5)$$

$$L_j = \left|1 + \frac{\underline{V}_{0j}}{\underline{V}_j}\right| = \frac{\underline{S}_j^{+}}{\underline{Y}_{jj}\underline{V}_j^{2}} \qquad (6)$$

The outcome of the presented theory is,

L<1, for stability to be guaranteed

B. ANN

Artificial neural networks have numerous applications to power system security. In this paper an investigation is carried out for the application of ANN to find the voltage stability Index- L using a developed training algorithm for all the buses in the system.

The neural network used here is a multi-layered back propagation Feed Forward Neural Network (BPFNN) where the L-index is the output for a predefined set of input variables which influence the most on voltage stability. The architecture of the proposed feed forward neural network consists of an input layer, a hidden layer and an output layer. Figure 1 shows the architecture of the proposed ANN trained using Levenberg-Marquardt training algorithm. The ANN consists of 3 neurons in the input layer, 12 neurons in the hidden layer and 1 neuron in the output layer.

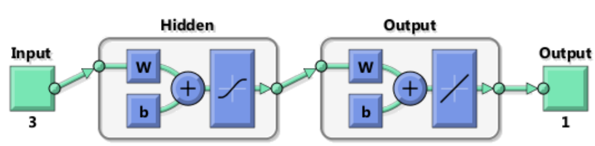

Figure 1 ANN Architecture for L-Index prediction

The training dataset for ANN consists of a total of 1200 data with different load buses and different real power loading and corresponding L-index. Out of 1200 data, 840 were used for training the network and 360 data were used for testing and validation of the network.

C. ANFIS

In the work presented in this paper an investigation is also carried out for the application of ANFIS to find the voltage stability Index- L using a developed training algorithm for all the buses in the system. The ANFIS is first given training data and after training the system untrained data are given and the corresponding outputs are obtained. Once when a suitable combination of network functions and parameters are found out this can be used online for practical power system networks. The setup even can be extended to be able to use in an energy management center for online establishment of voltage stability margin and to find out the limits of each bus.

The developed ANFIS to predict the L-index of IEEE 30 bus test system works under any real power loading condition. The architecture of the developed ANFIS is shown in Figure 2. The network is trained with 1200 data generating a total of 343 rules.

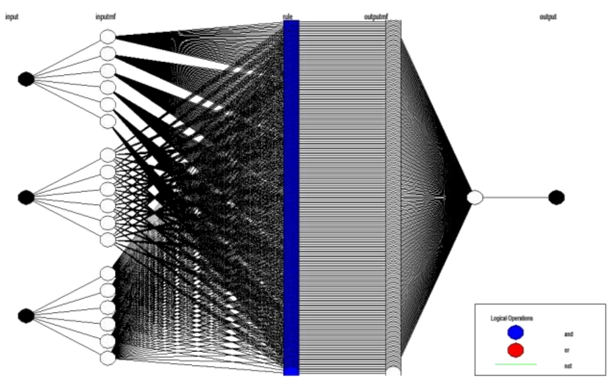

Figure 2 ANFIS Structure for L-index prediction

Each input of ANFIS (Bus Number, Real power load, reactive power load) are characterized using 4 triangular membership functions each and the output of ANFIS (L-index) is characterized using 4 constant membership function. Weighted Average defuzzification method is used to convert the output of ANFIS from linguistic variable to Actual value of L-index.

III. SIMULATION AND RESULTS

The proposed ANN and ANFIS based L-index for voltage stability assessment is tested on an IEEE 30 bus standard test case to analyse the reliability of the proposed method under different system architectures.

The IEEE 30 bus system consists of 1 slack bus, 5 PV buses and 24 PQ or load buses with 41 transmission lines for power evacuation to different places. The L-index estimated for all the load buses (For generator/PV and slack buses, the L-index is zero as this index is based on load variation).

The plot for L-index for this system for base case values is presented in Figure 3.

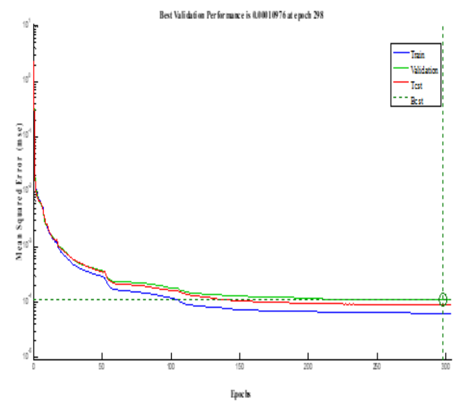

Figure 3 L-index value for all buses

The L-index values seen from Figure 3 shows that, for base loading in IEEE 30 bus test case, all buses are within the stable limits. However, bus 26 has the highest value of L-index (L26=0.5245) which means that this bus is prone to voltage instability compared to other buses with increase in real power demand.

To assess the L-index of load buses under any loading condition, an ANN is developed as described in previous section. The network is trained for minimal Mean Square Error (MSE) and Regression value of close to 1 which ensures excellent fitting of input-output variables. The performance characteristics and regression plot of ANN training are shown in Figures 4 and 5 respectively.

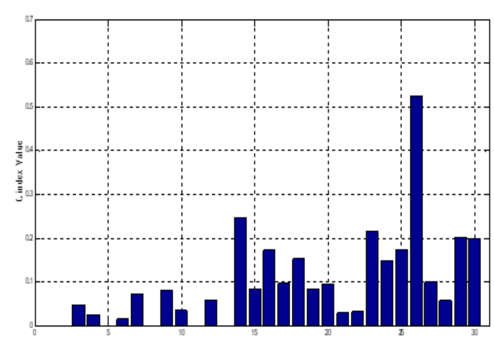

Figure 4 Performance characteristics of ANN

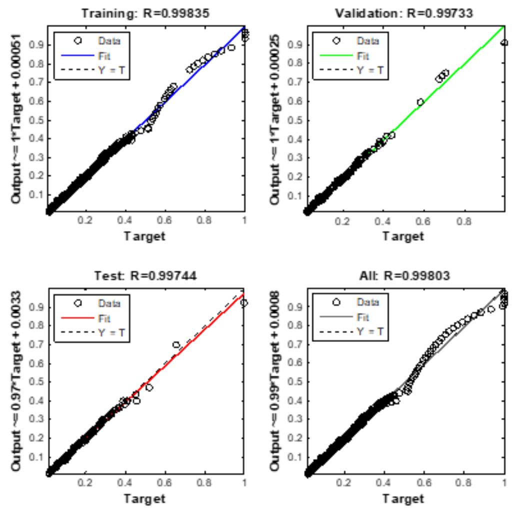

Figure 4 Performance characteristics

The trained network is further used to predict the value of L-index across various load buses under varying load condition. This is presented in Figure 5.

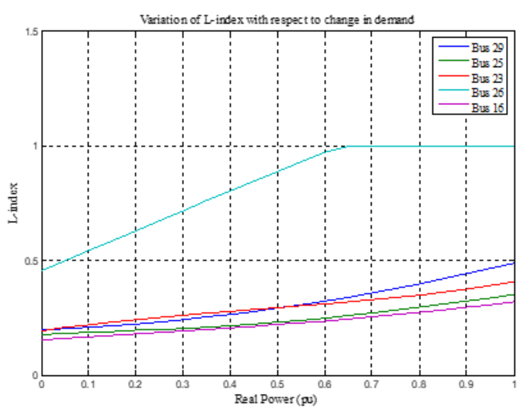

Figure 5 Impact of load variation on L-index using ANN

The results show that bus 26 is prone to voltage instability compared to other buses in the system. When the loading in the bus is increased gradually from 0 pu , the L-index gradually increases and reaches 1 at real power loading of 0.64 pu and the bus loses its stability. Hence this bus needs to be taken care by implementing suitable voltage control strategies.

Though ANN predicts the value of L-index with minimal errors, the acceptability of AI implementation for L-index is tested with another AI tool, ANFIS whose basic structure is presented in Figure 2. The inputs and output are classified into 7 membership functions each and a total of 343 rules are generated for getting the required output for IEEE 30 bus test case. The surface view relating the inputs and output of ANFIS is presented in Figure 6 that shows the nonlinear relationship between the inputs and output.

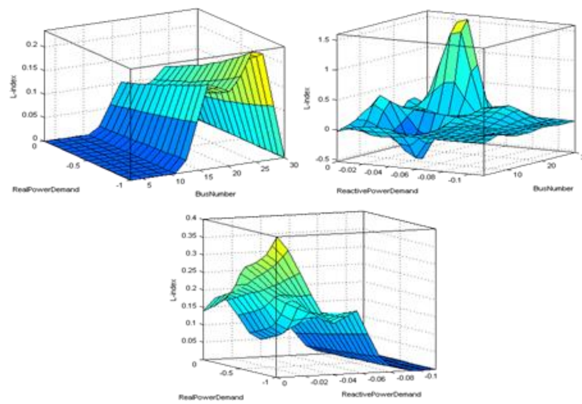

Figure 6 ANFIS Surface view

The ANFIS with 343 rules is trained with as error of 0.00452 in the L-index. The trained ANFIS is used to predict the L-index for real power load variation from 0 to 1 pu in all load buses in the test system. The results for buses 16,23,25,26 and 29 are presented in Figure 7.

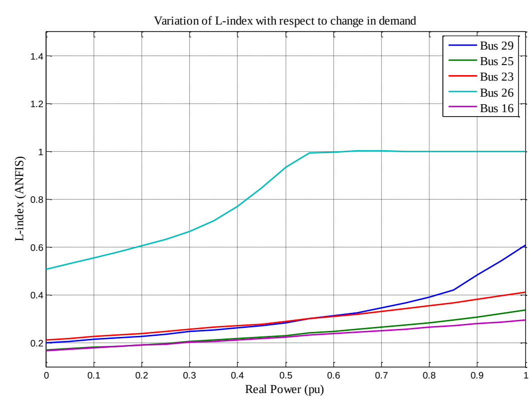

Figure 7 Impact of load variation on L-index using ANFIS

The results are similar to the one obtained using artificial neural network with slight variation. Bus 26 is observed to be prone to voltage instability compared to other load buses. The L-index of bus 26 gradually increases and reaches the unstable point at real power loading of 0.6 pu. Hence this bus needs to be taken care in implementing voltage stability enhancement techniques while comparing with other load buses.

IV. CONCLUSION

This work presented in this paper dealt with the application of AI techniques such as ANN and ANFIS to give the system operator a clear voltage stability measure. During the last few years, a lot of voltage stability indices were proposed, but usually they are strongly nonlinear and difficult to use for the system operators. The goal of this research is to translate one of such indices into a very easy to understand security measure through ANN and ANFIS.

The voltage stability index L is selected and used as a target output of ANN and ANFIS. This index chosen gives a significant accuracy and reliability in different operating conditions, especially when the power system is close to the voltage collapse. From the simulation results, it is observed that both ANN and ANFIS give required results with minimum error and the computational complexity is very much reduced when compared to conventional methods.

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