Detection of Proximity to Voltage Collapse Indicator Using Artificial Neural Networks

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Abstract— Modern power systems are currently operating under heavily loaded conditions due to various economic, environmental, and regulatory changes. Consequently, maintaining voltage stability has become a growing concern for electric power utilities. With the increased loading and exploitation of the power transmission system, the problem of voltage stability and voltage collapse attracts more and more attention. A voltage collapse can take place in systems and subsystems, and can appear quite abruptly. There are different methods used to study the voltage collapse phenomenon, such as the Jacobian method, the voltage instability proximity index (VIPI) and the voltage collapse proximity indicator method. This paper is concerned with the problem of voltage stability, and investigates a proposed voltage collapse proximity indicator applicable to the load points of a power system. Voltage instability is early predicted using artificial neural networks on the basis of a voltage collapse proximity indicator. Different system loading strategies are studied and evaluated. Test results on a sample and large power system demonstrate the merits of the proposed approach. The objective of this paper is to present the application of ANN in estimating the voltage collapse proximity indicator of a power system.

Index Terms— Power Systems, Voltage Security, Voltage Instability, Voltage collapse and Neural Networks

1 Introduction

Progressive energy demands associated with shortage in installed capacities have resulted in the power systems to be operated at or close to their security limits. These limits are, generally, related to the problems of thermal loading and transient stability. Modern control and protection equipment have raised the transfer limits in stability limited systems. However, as the operating conditions for large power systems have evolved, a new type of problem has been observed. This phenomenon is referred to as voltage instability or voltage collapse. It is characterized by a continuous decline of voltage, which can occur due to the inability of the network to meet the increasing demand for reactive power.

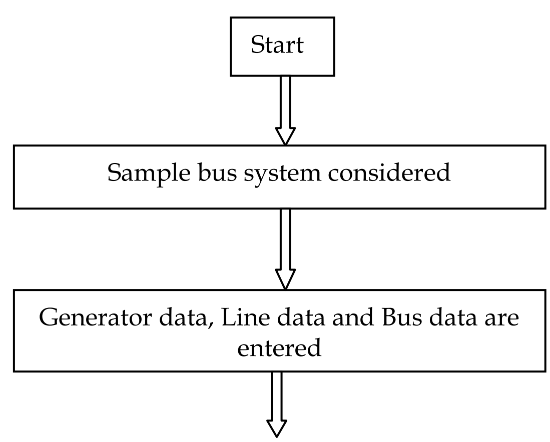
Available methods for voltage stability assessment are usually classified into static and dynamic methods. Static methods assume a steady state model or a linearized dynamic model to investigate the state of the equilibrium point of a specified operating condition of the power system. For Dynamic methods, the solution of the governing equations is carried out in the time domain and the study period is in the order of several minutes. Dynamic simulations are time consuming and do not readily provide sensitivity information and degree of stability. A number of indices of static voltage stability have been proposed in literature to quantify the proximity of the power system to voltage collapse. Among the most widely used voltage stability indices are the voltage collapse proximity indicator, the minimum singular value of the power flow Jacobian matrix, and loading margin.

Voltage collapse proximity indicators are usually considered as useful measures of the closeness of the power system to the collapse point. For a particular operating point, the value of the indicator provides information of each bus voltage and its proximity to the voltage collapse limits. However, as the operating condition of a power system continuously changes, it is difficult to use these methods to provide real time information due to the significant computational requirements of such methods. Artificial Neural Networks (ANN) computational schemes have been successfully applied in loading margin estimation, optimization of electrode contour and security assessment. ANN with their ability to provide non-linear input/output mapping, generalization, and abstraction have the potential to estimate the voltagecollapse proximity indicator of a power system without solving the governing power system equations.

2. Proposed Methodology

The method implemented in this paper is represented as a flowchart Fig. 1. Each block in the figure explains the steps involved in computing L-index value.

From the given network topology, generation and load data; [FLG] matrices are computed. Power flow are run. From the value of [FLG] with voltage magnitude at each bus, L-index values are computed.



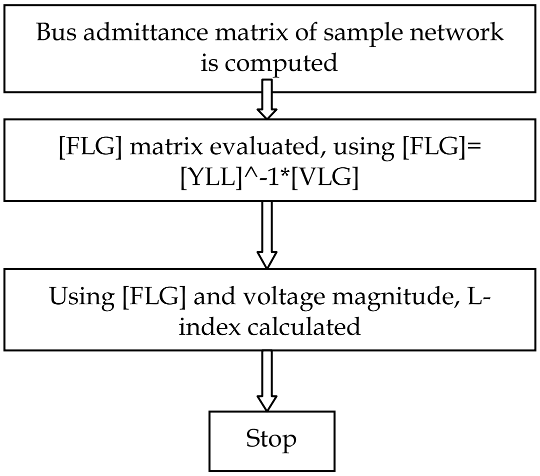


Fig 1. Flow chart of proposed technique

3. Methods to Estimate Voltage Collapse Indicators

Different indicators have been proposed to assess the proximity of the system to voltage collapse.

The Jacobian Method This method was the first to relate power system stability to the load flow Jacobian. In this work, it is shown that, with some assumptions (P and V are specified for all generator buses, neglecting damping for all of the generators) and using Newton-Raphson method in the polar form, the determinant of the load flow Jacobian becomes equal to the product of the eigenvalues of the system. This means that when a change takes place in the sign of the determinant, at least one of the Eigen values has crossed the imaginary axis from the stable to the unstable side.

Voltage Instability Proximity Index Power flow equations typically present multiple solutions, with one of these solutions corresponding to an "operable" point of a power system. It is known that the number of existing solution decreases as operating point approaches the collapse point and only a pair of solutions remain near the collapse point and then coalesces onit. The Voltage Instability Proximity Index (VIPI) is used to predict proximity to voltage collapse using this solution pair.

Voltage Collapse Proximity Indicator The Voltage Collapse Proximity Indicator (VCPI) was introduced by Kessel and Glavitch for a two-bus system model and was generalized for a multi node system using a hybrid model for the power system. This indicator utilizes the information obtained from a normal load flow solution. The method can be used to determine local indicators corresponding to each load bus. The indicator L varies in the range between 0 (no load of system) and 1 (voltage collapse) values close to one indicate proximity to power flow divergence. Based on the concept, various models are derived which allow the predicting of voltage instability or the proximity of a collapse under various contingencies such as loss of generators or lines as well as load variations. The advantage of the method lies in the simplicity, reliability and it can give a good indication about the critical power a system can maintain before collapse over the whole region and for all the cases studied. A local indicator j L for each node j can be calculated as explained below:

consider a system where n be the total number of buses with 1,2,…,g be the generator buses, and g+1,…,g+s, be switchable VAR compensator (SVC) buses, g+s+1,…, n be the remaining (n-g-s) load buses. Using the load flow results, the L-index value, computed at load buses is given as

$$Lj = 1 - \sum_{i=1}^{i=g} Fji \times Vi \div Vj$$

The value of L-index lies between 0 and1. An L-index value less than 1 (unity) and close to 0 (zero) indicates an improved voltage stability margin. The values Fji are obtained from the Y-bus matrix given by ([FLG])

4. Case Study

The IEEE 6 bus system is considered for the study which consists of 6 buses, 3 generators, 11 transmission lines and 3 loads. The power flow analysis is carried out by considering bus one as slack bus. The data for the system are on 100 MVA base.The load data and bus data are given in table 3.1 and 3.2.

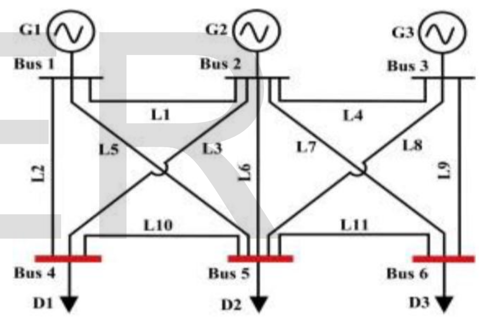


Fig 2. IEEE six bus system

Table 1. Line Data

Branch No	From Bus	To Bus	R	X	Line Limit
1	1	2	0.1	0.2	40
2	1	4	0.05	0.2	60
3	1	5	0.08	0.3	40
4	2	3	0.05	0.25	40
5	2	4	0.05	0.10	80
6	2	5	0.1	0.30	30
7	2	6	0.07	0.20	90
8	3	5	0.12	0.26	70
9	3	6	0.02	0.10	90
10	4	5	0.2	0.40	20
11	5	6	0.1	0.30	40

TABLE 2.BUS DATA

Bus No	Type	Voltage	Pd	Pg	Qg	Qd	Qmax	Qmin
1	Slack	1.05	0	1	-	0	-0.2	1
2	PV	1.05	0	0.5	-	0	-0.2	1
3	PV	1.07	0	0.6	-	0	-0.15	1
4	PQ	1	0.7	0	0	0.7	0	0
5	PQ	1	0.7	0	0	0.7	0	0
6	PQ	1	0.7	0	0	0.7	0	0

5. ANALYSIS USING ARTIFICIAL NEURAL NETWORK

The multi-layer feed-forward NN, also known as the multi-layer perceptron (MLP) NN, is use in this work. It is characterised by its architecture, activation functions, training and learning algorithm It consists of an input layer, output layer, and one or more hidden layers. The output and the hidden unit may have bias. The bias is denoted by bj and bk. Data from the input layer flow through the hidden layer to the output layer. The layers are interconnected by communication links represented as weight. The weights are determined by training algorithm. One of the popular training algorithms for the MLP NN is the error back propagation algorithm, which is based on the gradient descent technique for error reduction. In this paper, we used the MATLAB neural network toolbox to train the MLP NN with back-propagation technique. The weight and biases are adjusted iteratively to achieve a minimum mean square error between the network output and target value.

Recently, there has been considerable interest in the application of Artificial Neural Network (ANN) to power system. ANN has the ability to classify complex relationships properly. The relationships classified by ANN are highlynon linear and often result from large mathematical models. Once trained, the ANN can classify new data much faster than it would be possible by solving the model analytically: An integrated based systems, ANN, and conventional power system solution methodologies have potential to provide real-time optimization and control of power system. This paper presents the application of ANN to for proximity to voltage collapse.

6 RESULTS AND DISCUSSION

6.1 Data set Preparation:

Thirty values of percentage of load level are considered as input and using MATLAB code corresponding L-index La, Lb, Lc of system are determined and L-indices are considered as targets. Such data is used for training fitting tool of ANN toolbox using MATLAB. Once the ANN is trained the same can be used to determine the L-index values for new input.

TABLE 3. LOAD LEVEL AND L-INDEX VALUES

Load Level in pu	La	Lb	Lc
0.60	0.0544	0.0709	0.0596
0.62	0.0518	0.0669	0.0552
0.64	0.0511	0.0651	0.0523
0.66	0.0513	0.0661	0.0534
0.68	0.0461	0.0554	0.0418
0.70	0.0478	0.0576	0.0435
0.72	0.0496	0.0598	0.0452
0.74	0.0514	0.0621	0.0469
0.76	0.0532	0.0644	0.0487
0.78	0.0551	0.0667	0.0506
0.80	0.0569	0.0691	0.0524
0.82	0.0589	0.0716	0.0544
0.84	0.0608	0.0741	0.0564
0.86	0.0628	0.0767	0.0584
0.88	0.0649	0.0794	0.0605
0.90	0.0669	0.0821	0.0626
0.92	0.0691	0.0849	0.0648
0.94	0.0712	0.0877	0.0671
0.96	0.0735	0.0907	0.0694
0.98	0.0757	0.0937	0.0716
1.00	0.0780	0.0968	0.0743
1.02	0.0804	0.1000	0.0768
1.04	0.0829	0.1033	0.0795
1.06	0.0854	0.1067	0.0822
1.08	0.0879	0.1102	0.0851
1.10	0.0906	0.1138	0.0880
1.12	0.0933	0.1175	0.0911
1.14	0.0961	0.1214	0.0942
1.16	0.0989	0.1254	0.0975
1.18	0.1019	0.1296	0.1010
1.20	0.1050	0.1340	0.1045

7. TRAINING ANN USING MATLAB

In the welcome window of ANN toolbox fitting tool app is selected as shown in the figure3.

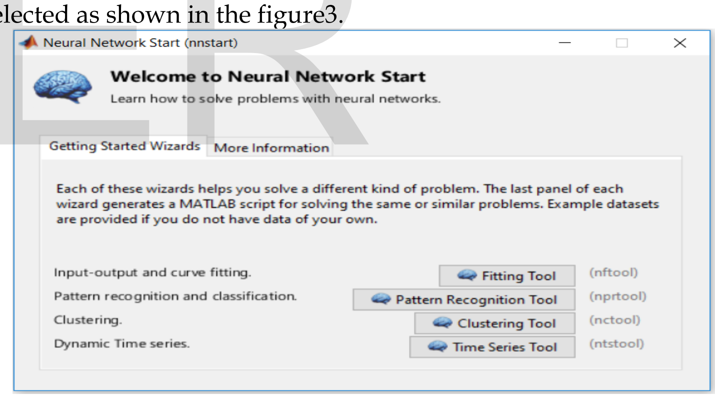


Fig 3. Neural Network Start

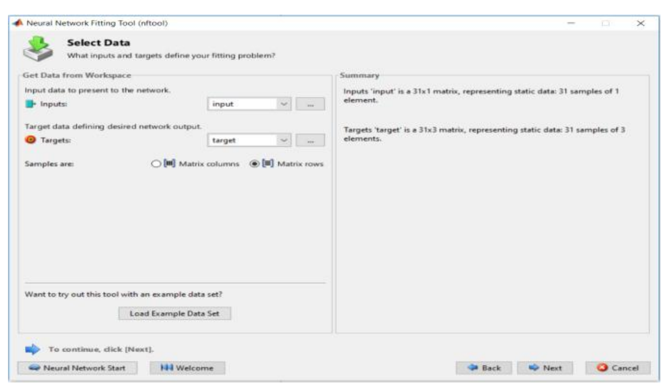


Fig 4. Importing data to the network

The input and target sets are prepared by considering 31 load conditions, corresponding load levels are considered as inputs and L-index are considered as outputs and data sets are loaded first to excel sheet and then they are imported to MATLAB for training an ANN. The sizes of both matrices are 31*1 and 31*3 as there are 6 buses.

After importing the data ANN is trained using Levenberg Macquardit algorithm. The correctness of the trained network is ensured by using Mean square error and regression value. The regression value near one shows that ANN is trained correctly and hence it can be used to produce the results for new set of data.

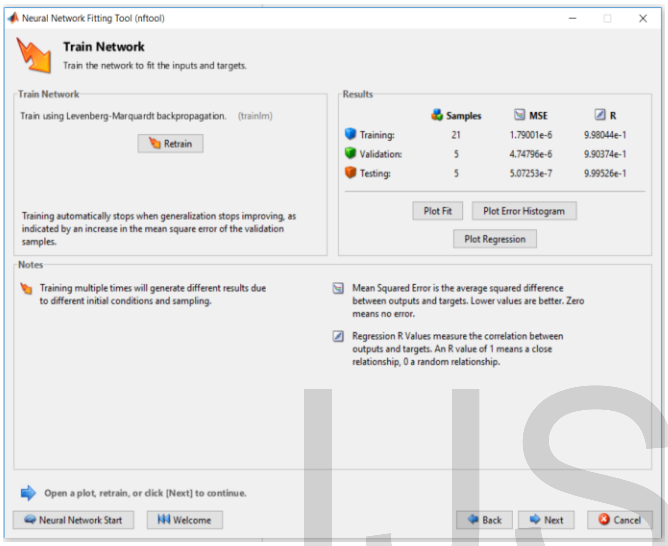


Fig 5. Training Neural Network

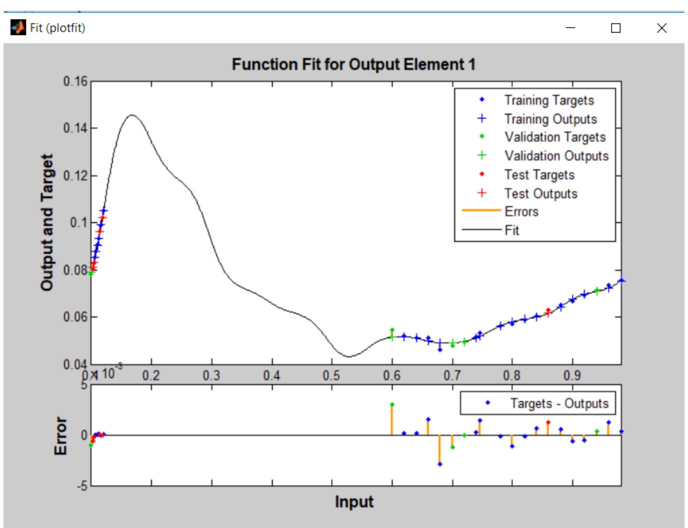


Fig 6. Plot Fit

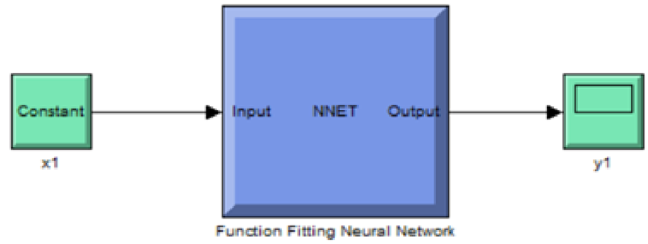


Fig 7. Simulink Diagram

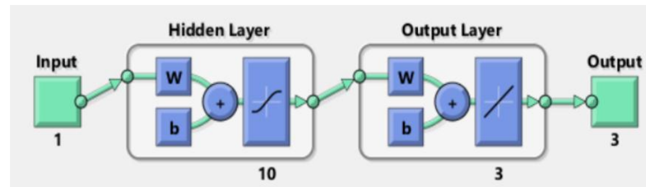


Fig 8. Trained Neural Network

Results

	Samples	MSE	R
Training:	21	1.79001e-6	9.98044e-1
Validation:	5	4.74796e-6	9.90374e-1
Testing:	5	5.07253e-7	9.99526e-1

Fig 9. Results of 31 Load Levels

It can also be observed that with increased data size the performance of the network still improved both in terms of regression and mean squared error.

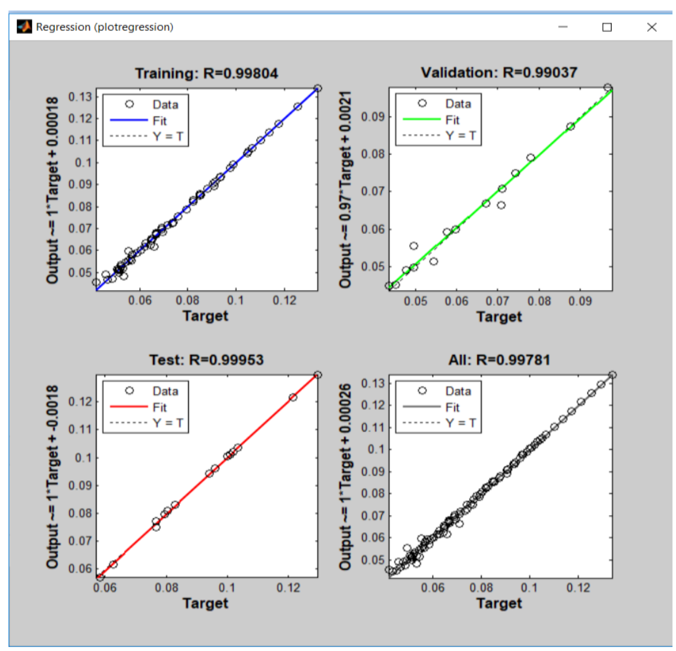


Fig 10. Regression Plot

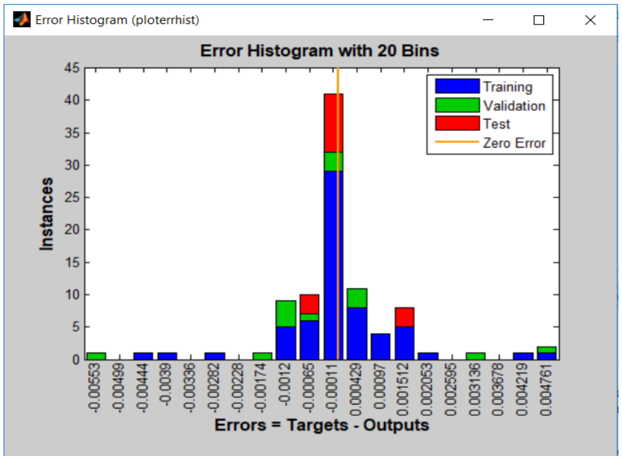


Fig 11. Error Histogram

8. CONCLUSION

Proximity to voltage collapse is an important ascept of power system operation has been explained in this paper using ANN toolbox of MATLAB. An IEEE 6 bus system is considered, executed using MATLAB code and results are used to train the ANN. L-index value for different load level is tabulated

The L-index voltage stability provides a review of voltage stability of the system at any given operating point. Higher value of L-index indicative of most critical buses and thus maximum of L-indices is an indicator of proximity in the system to represent voltage collapse, than corrective action takes place to maintain system stability.

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