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Application of ANN Technique for Identification of Critical Bus and Branch

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Abstract

This paper presents to identify critical buses and critical lines using Artificial Neural networks (ANN). Universally the demand for the electric power is being increased under this situation power system problems (i.e., lack of reactive power, overloading, faults, etc.) are encountered. In this paper the Line L-Index and Voltage Collapse Proximity Index (VCPI) has been used to find out a critical bus, Line Voltage Stability Index (L_{mn}) is used ~~t~~o find out the critical branch of the system. ANN has been used to reduce computational complexity and time. For this purpose, MATLAB software and IEEE-14 bus system have been used under single transmission line outage contingency condition.

Keywords: *Voltage instability, L-Index, L_{mn}, VCPI, line outage, ANN*

1. Introduction

In general, heavily loaded networks due to voltage stability problems in power system. "Voltage stability [1] is a concern with the ability of power system to maintain the acceptable voltage at the all buses in the power system under normal and being subjected to a disturbance". The main source of instability is that the deficiency of reactive power. Voltage stability is classified into four categories, they are large disturbance voltage stability (*e.g.,* faults, loss of generation, circuit failures), small disturbance voltage stability (this is influenced by characteristics of loads), sort term voltage stability (*e.g.*, Induction motors, HVDC converters), and long-term voltage stability (*e.g.*, Tap changing transformers, thermostatically controlled loads).

Distinct types of Voltage stability indices [2-7] are available in literature used to evaluate the stability margin of the power system. These are L-Index (LI) [8], voltage Collapse Proximity Indicator (VCPI) [9], Line voltage stability index (L_{mn}) [10-12], Fast VSI [13], and Voltage stability index (VSI). Among all the indices VCPI and L_{mn} gives consisting results [14-15]. Voltage stability indices are special tools to quantifying the proximity of a given driving point to voltage instability. The outline of voltage stability indices is used to evaluate driving a point of the steady-state voltage stability margin.

In recent years ANN [16-22] are widely used in most of the applications such as Medicine, Image processing & computer vision, Pattern recognition, Signal processing, Planning, control & search, Power systems *etc*. In this paper, the application of Artificial Neural Networks (ANN) is used to find the critical bus and critical branch.

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2. L -Index

A technique called L-Index was proposed to be used in estimating voltage instabilities of the power system [8]. This method uses the phasor information and no-load voltage at the bus to calculate L-Index. The features of L-Index are (a) Identification of weak system states, (b) Uninterrupted calculation of the actual system state, (c) Identification of severe locations in the system and (d) Forecast the voltage collapse under several contingencies such as outage of generators or lines or buses as well as load variations. The L-Index ranging from 0 to 1. The L-Index at the jth bus is given by

$$L_j = \left|1 + \frac{V_{0j}}{V_j}\right| = \frac{S_j^{*}}{Y_{jj} V_j^{2}} \tag{1}$$

where

S_j^{*} = Complex power at jth bus.

V_j = Voltage at jth bus.

Y_{jj} = Bus admittance.

V_{0j} = Corresponding generator voltage including the involvement after all Generators.

3. Line Voltage Stability Index (L_{mn})

A voltage stability technique was developed based on a transmission network perception [9-11]. In this case, all the power transmission network is compact to the single-line network to evaluate the stability of power system. Consider a single-line representation of transmission network of the power system as shown in Figure 1.

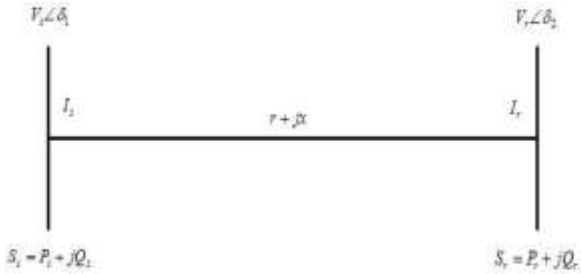

Figure 1. Single-line Representation of Transmission Network

The complex power at the receiving and sending end for the given transmission line in Figure 1 considering as the nominal-π model is given below in equation (2) and (3).

$$S_r = \frac{|V_s||V_r|}{Z} \angle(\theta - \delta_1 + \delta_2) - \frac{|V_r|^2}{Z} \angle\theta \tag{2}$$

$$S_s = \frac{|V_s|^2}{Z} \angle\theta - \frac{|V_S||V_r|}{Z} \angle(\theta + \delta_1 - \delta_2) \tag{3}$$

The receiving end active and reactive power are given in equation (9) to (10)

$$P_r = \frac{V_s V_r}{Z} \cos(\theta - \delta_1 + \delta_2) - \frac{V_r^2}{Z} \cos\theta \tag{4}$$

$$Q_r = \frac{V_s V_r}{Z}\sin(\theta - \delta_1 + \delta_2) - \frac{V_r^2}{Z}\sin\theta \tag{5}$$

Putting $\delta_1 - \delta_2 = \delta$ in equation (5) and solve for V_r

$$V_r = \frac{V_s \sin(\theta-\delta) \pm \left\{[V_s \sin(\theta-\delta)]^2 - 4ZQ_r \sin\theta\right\}^{0.5}}{2\sin\theta} \tag{6}$$

Put $Z\sin\theta = X$ in equation (6), we have

$$V_r = \frac{V_s \sin(\theta-\delta) \pm \left\{[V_s \sin(\theta-\delta)]^2 - 4XQ_r \sin\theta\right\}^{0.5}}{2\sin\theta} \tag{7}$$

In order to obtain V_r and Q_r the equation should have real roots. Thus, the subsequent conditions, which might be used as a stability criterion, must be satisfied:

$$\left\{[V_s \sin(\theta-\delta)]^2 - 4XQ_r\right\} \geq 0 \qquad \text{Or}$$

$$\frac{4XQ_r}{[V_s \sin(\theta-\delta)]^2} = L_{mn} \leq 1.00 \tag{8}$$

4. VCPI

V. Balamourougan *et. al.*, [12] has proposed a technique through Voltage Collapse Proximity Indicator (VCPI) for online voltage stability monitoring. The technique comes from the fundamental power flow equation. The following features of VCPI are

1) This technique calculates the voltage collapse proximity index.
2) VCPI contains the effect of loads at all buses when calculating the voltage collapse index at a specific bus.
3) VCPI needs only less number of calculations for estimation of the voltage collapse proximity index at a bus.
4) It needs voltage phasor information and network impedance at buses for calculating VCPI.
5) This technique can be used to help with real-time operations, designing and system planning.
6) For any number of buses in a system, this technique is applicable.

For an N-bus system, the complex power at bus k is given by,

$$S_k^* = |V_k|^2 - (|V_k|\cos\delta_k)\_\ j|V_k|\sin\delta_k \left[\sum_{\substack{m=1\\m\neq k}}^{N} (|V_m'|\cos\delta_m' + j|V_m'|\sin\delta_m'\right] Y_{kk} \tag{9}$$

V_m' in equation (9) is given by

$$V_m' = \frac{Y_{km}}{\sum\limits_{\substack{j=1\\j\neq k}}^{N} Y_{kj}} V_m \tag{10}$$

The R.H.S. of equation (10) is an apparent quantity, which is in the form a-jb. The two unknowns (V_k, δ) can be written from following two equations as

$$f_1(|V_k|, \delta) = |V_k|^2 - \sum_{\substack{m=1\\m\neq k}}^{N} |V_m'||V_k|\cos\delta \tag{11}$$

$$f_2(|V_k|,\delta) = \sum_{\substack{m=1 \\ m\neq k}}^{N} |V_m^{'}||V_k|\sin\delta \tag{12}$$

By solving above two equations (11) & (12) for calculating the (V_k , δ) using the NR power flow method technique, a derivative function matrix is obtained. The determinant of the matrix is identical to zero at voltage collapse leading to the subsequent equation.

$$\frac{|V_k|\cos\delta}{\sum\limits_{\substack{m=1 \\ m\neq k}}^{N} |V_m^{'}|} = \frac{1}{2} \tag{13}$$

Manipulating the equation (13), at kth bus the voltage collapse prediction index (VCPI) is developed and is given by

$$VCPI_{k^{th}bus} = \left| 1 - \frac{\sum\limits_{\substack{m=1 \\ m\neq k}}^{N} V_m^{'}}{V_k} \right| \tag{14}$$

The above equation (14) gives that the condition for voltage collapse at the kth bus.

5. Flow Chart

The proposed flowchart can be used to find out the critical Bus and Branch in the system.

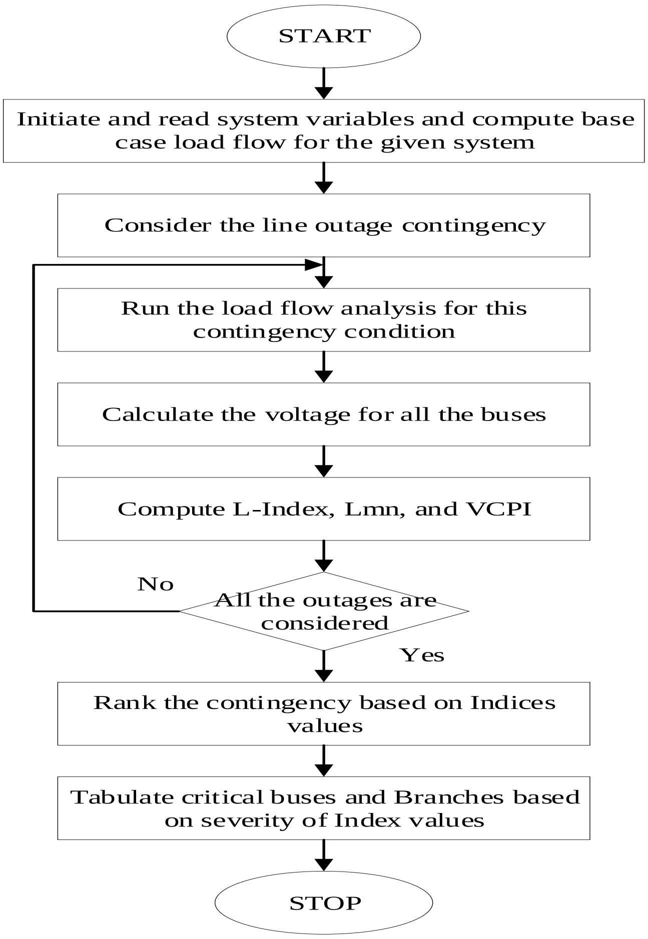

Figure 2. Flowchart Identification of Critical Bus and Critical Branch

6. Architecture of Artificial Neural Network

Multi-layer feed forward neural network is depicted in Figure 3. The objective of the neural network is recognition and data compression can effectively have implemented. It consisting of three layers i.e., input layer, hidden layer, and output layer.

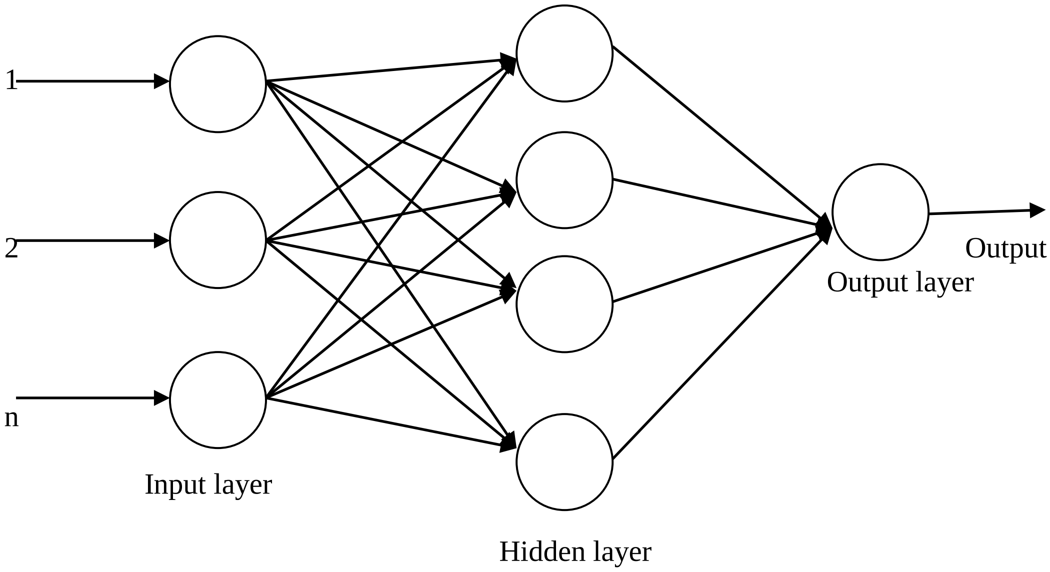

Figure 3. Neural Network Architecture

7. NN for Power Systems

A bulk range of power system issues shares a group of common features that create them aspirants for neural network solutions. Following are some of the key attributes.

- Power system issues may have to frequently work out within the hour to hour operation and management of power systems. The recurrence of determination relies upon the operational many-sided quality of the real utility.
- Predictable resolution techniques could also be computationally escalated and time intensive. This technique spends extreme time on the energy management system computers of the value of different computations.
- Exact mathematical modeling might not be possible due either to the quality or to the dearth of accessible info concerning the matter.
- Available information might not be during a purposeful type, however rather within the sort of historical input/output examples.
- Operational conditions might be clamant.

Neural networks (NN) offer the following advantages that can help effectively deal with some of the above mentioned difficulties. They are:

- Neural Networks has the flexibility to find out and develop an opulent nonlinear mapping through a collection of input or output examples. The specification permits simple coaching while not a requirement for the structured model.
- Input variables are often simply side or deleted. Correlative or unrelated knowledge are often used.
- Neural Networks has prevalent commotion dismissal capacity which will adequately subsume vulnerabilities of the specific technique.
- Neural Networks executes in the blink of an eye.
- NN comprises a curiously large scope of information handling units which may be implemented misuse broadly useful neural system equipment. Along these lines, it is frequently mitigating the weight of calculation from vitality administration framework PCs.

Before neural networks will gain recognition as helpful drawback finding tools within the power trade, sure basic problems have to be compelled to be addressed. A number of them square measure related to neural network fundamentals. Others square measure drawback dependent and square measure listed below:

- Determining the right consistency of the coaching and testing knowledge sets as well as the number of patterns, input and output dimensions, and applied math properties. So as to produce adequate generalization and information retention.
- The use of feature selection and clustering techniques for data preprocessing. This can help achieve to reduction in both dimension and combinatorial complexity.

8. Flow Chart

The proposed flow chart can be used for Test and Train the data in the given IEEE-14 bus system.

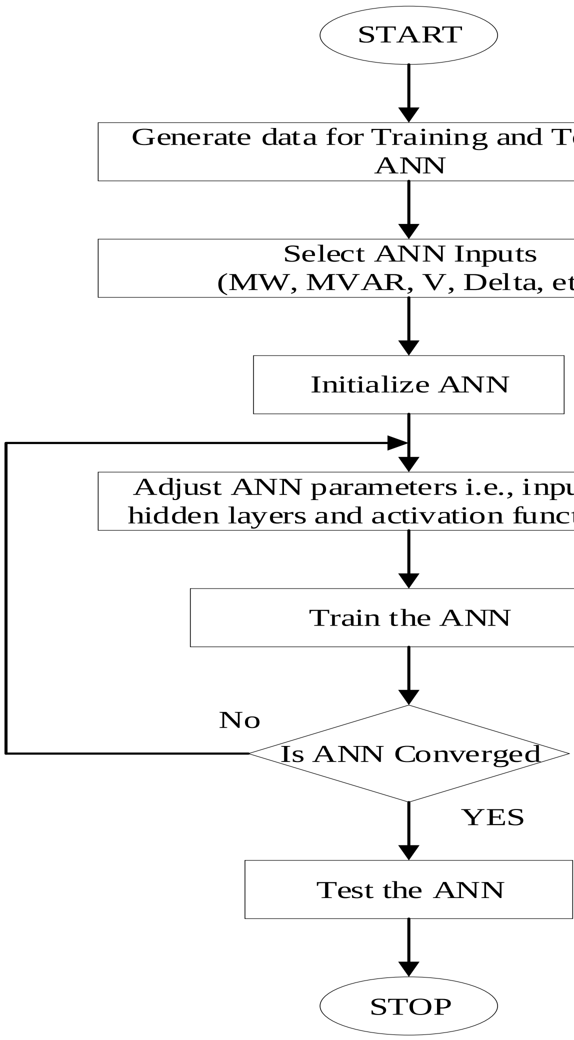

Figure 4. Implementation of ANN

From the above flowchart, the primary step is to run the NR power flow with Stability indices program with varying system load *i.e.*, overall active and reactive power. After completion of load flow, the data is automatically stored in the workspace or separately recorded in Excel sheet. This data is training, testing and validating by using neural network tool in MATLAB.

9. Case Study

In this case, the IEEE-14 bus system is considered for the simulation purpose. L-Index, VCPI and Line voltage stability index (L_{mn}) are used to evaluate voltage stability at a power system bus and lines.

"Do not consider the line which is connected with the slack bus as a most severe line / or make it as the most important line which should not get outage".

The study has been carried out in four different cases as mentioned below:

Case 1. Critical Bus Ranking through L-Index under system loading condition for Contingency case

Case 2. Critical Bus Ranking through VCPI under system loading condition for Contingency case

Case 3. Critical Line Ranking through L_{mn} under system loading condition for Contingency case

Case 4. ANN using prediction of weak bus and branch

Case1: Critical Bus Ranking through L-Index under system loading condition for Contingency case

Table 1. Critical Bus Ranking through L-Index under Different Loading Conditions

CBR	100% Loading			120% Loading			140% Loading			160% Loading		
	Bus No	Cont. No	LI	Bus No	Cont. No	LI	Bus No	Cont. No	LI	Bus No	Cont. No	LI
1	4	17	0.249562	4	17	0.338499	4	1	0.692363	4	1	3.868691
2	9	17	0.201843	9	17	0.276057	9	1	0.438305	5	1	1.006098
3	14	17	0.124034	14	17	0.169042	14	1	0.286812	7	1	0.899075
4	13	17	0.12306	13	17	0.168001	13	1	0.25227	9	1	2.980188
5	10	17	0.109316	10	17	0.149769	10	1	0.251429	10	1	1.615402
6	5	17	0.095776	5	17	0.130255	5	1	0.222455	11	1	1.074809
7	12	17	0.091275	12	17	0.124722	12	1	0.187702	12	1	1.231385
8	11	17	0.082441	11	17	0.112925	11	1	0.185324	13	1	1.695722
9	7	17	0.067939	7	17	0.093465	7	1	0.145893	14	1	2.092705

Table 1 demonstrates the Critical Bus Ranking in light of the L-Index for IEEE-14 bus system. The utmost critical bus for 100%, 120%, 140%, 160%, is 4, 4, 4, 4 and L-Index is 0.249562, 0.338499, 0.692363, and 3.868691 respectively.

Case2: Critical Bus Ranking through VCPI under system loading condition for Contingency case

Table 2. Critical Bus Ranking through VCPI under Different Loading Conditions

CBR	100% Loading			120% Loading			140% Loading			160% Loading		
	Bus No.	Cont. No	VCPI	Bus No.	Cont. No	VCPI	Bus No.	Cont. No	VCPI	Bus No.	Cont. No	VCPI
1	11	1	0.272537	12	10	0.299884	11	1	0.323338	12	10	0.344539
2	9	1	0.265514	13	10	0.296856	9	1	0.317031	13	10	0.339768
3	13	1	0.261039	11	10	0.28165	13	1	0.313969	11	10	0.316738
4	10	1	0.260752	9	20	0.245382	10	1	0.313171	14	10	0.257691
5	12	1	0.257816	7	7	0.238973	12	1	0.310826	10	10	0.257428
6	7	1	0.249901	8	7	0.238394	7	1	0.297962	9	20	0.254564
7	8	7	0.23877	10	20	0.233747	14	1	0.291768	8	7	0.235038
8	14	1	0.234094	14	10	0.223783	4	1	0.25789	7	7	0.252999
9	6	20	0.22526	6	20	0.210645	8	7	0.237115	6	20	0.209176
10	4	1	0.212002	2	20	0.209993	6	20	0.218911	4	7	0.203183
11	2	20	0.209935	4	7	0.193996	2	20	0.210696	2	20	0.192717
12	1	2	0.208656	5	20	0.191617	5	1	0.208892	5	20	0.185901
13	5	20	0.192801	1	2	0.191162	1	20	0.170984	1	20	0.176356
14	3	20	0.182969	3	20	0.165116	3	20	0.174856	3	20	0.16356

Table 2 shows the Critical Bus Ranking in light of the VCPI for IEEE-14 bus system. The most critical bus for 100%, 120%, 140%, 160%, is 11, 12, 11, 12, and VCPI is 0.272537, 0.299884, 0.323338, and 0.344539 respectively.

Case3: Critical Line Ranking through L_{mn} under system loading condition for Contingency Case

Table 3. Critical Line Ranking through Lmn under Different Loading Conditions

CLR	100% Loading			120% Loading			140% Loading			160% Loading		
	Line No.	Cont. No	L_{mn}	Line No.	Cont. No.	L_{mn}	Line No.	Cont. No.	L_{mn}	Line No.	Cont. No.	L_{mn}
1	9	15	0.263241	9	15	0.289042	6	3	0.296324	3	6	0.505491
2	14	2	0.185943	14	2	0.223801	9	15	0.295587	3	7	0.404861
3	14	10	0.176103	6	3	0.220204	20	10	0.292649	3	2	0.387186

4	14	4	0.16619	20	10	0.214462	3	6	0.290369	6	3	0.38506
5	14	11	0.16267	14	7	0.204777	3	2	0.264477	18	10	0.371956
6	14	20	0.161747	14	4	0.19904	14	7	0.258441	3	4	0.347032
7	14	6	0.159795	14	5	0.198263	14	11	0.257521	14	11	0.3262
8	14	8	0.155903	14	13	0.198012	14	4	0.248077	14	18	0.30602
9	14	9	0.155747	14	18	0.190063	14	13	0.242466	14	13	0.304789
10	14	18	0.153693	14	17	0.186878	14	18	0.24176	9	15	0.301993
11	14	5	0.153128	14	20	0.185789	14	20	0.238307	14	20	0.301292
12	14	3	0.152713	14	8	0.182205	14	9	0.232242	14	9	0.287535
13	14	7	0.149854	14	9	0.180905	14	5	0.226968	14	5	0.272928
14	14	13	0.148185	14	11	0.174345	14	8	0.223826	14	8	0.265986
15	14	12	0.14429	14	12	0.173491	14	12	0.210086	14	12	0.262606
16	14	19	0.142572	14	19	0.17112	14	19	0.206996	14	19	0.258671
17	14	17	0.142097	14	16	0.170521	14	16	0.200312	14	16	0.254526
18	14	16	0.141031	14	6	0.166499	14	17	0.190332	14	17	0.231144

Table 3 shows the Critical line ranking in light of the L_{mn} for the IEEE-14 bus system. The most critical line for 100%, 120% 140%, 160% is 9, 9, 6, 3 and L_{mn} is 0.263241, 0.289042, 0.296324, and 0.505491 respectively.

Case 4: ANN using Prediction of Weak Buses and Branch

In this paper, to understand the robustness of Artificial Neural Network (ANN) without embedding FACTS device in the system using the IEEE-14 bus system. The critical bus ranking and line ranking is obtained.

In this paper, Levenberg-Marquardt Algorithm is used to train the data of the system. It is the mixture of Gradient descent and Newton methods. The network is trained by L-M backpropagation algorithm [17]. Once generalization stops up, as denoted by a rise within the Mean Sq. Error (MSE) of the esteem samples then, the training is automatically stopped. The MSE is that the average square distinction between outputs and targets. Lesser values are more excellent whereas zero gives no error. The execution of the proposed network is trained with LM back propagation algorithm using MATLAB R2015b and the performance is shown in Figure 5.

To choose the best architecture for the given problem a number of trial and error simulations were carried out and finally it was found that an input layer with 35 neurons and 2 hidden layers with 10 neurons and an output layer with one neuron was found to give the best performance. Backpropagation algorithm is used to train the network considering 90 training patterns and the network is tested for another 10 patterns. The ANN architecture of the ANN is given in Table 4. All the simulations are carried out in this work using MATLAB software in the Core 2 Duo system with a clock speed of 2.00 GHz.

Table 4. ANN Architecture for IEEE-14 Bus System

Type of ANN Parameter	Number used
No. of input neurons	35
No. of Hidden Layers	2
No. of neurons in hidden layers	10
No. of output layers	1
Error goal	0.001
Learning rate	0.4
Minimum performance gradient	1e-7

Critical Bus Ranking through L-Index under system loading condition for Contingency case

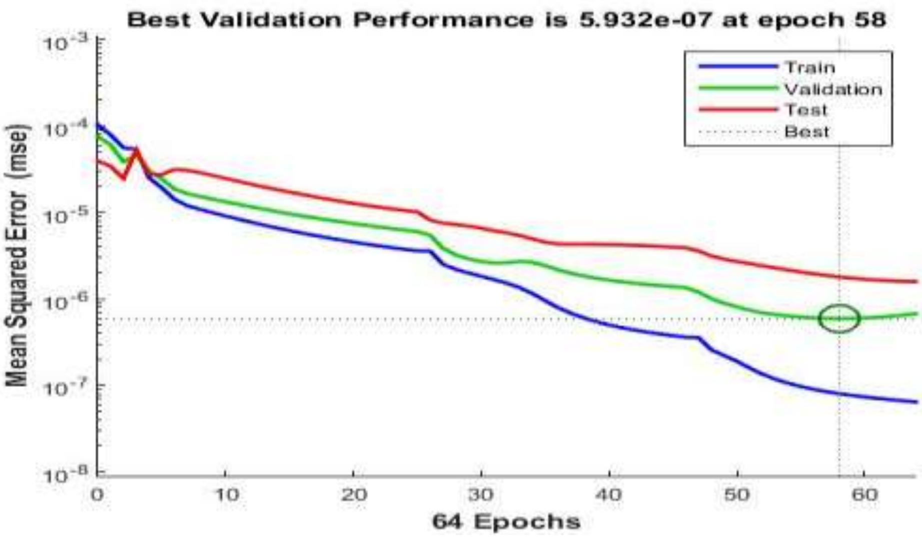

Figure 5. Performance of ANN for IEEE-14 Bus System under Contingency Condition for L-Index

At epoch number 58 it is viewed that the best validation performance is 5.932e-07 and as shown in Figure 5.

Table 5. Performance of ANN with LI

Actual Value	Predicted Value	Error
0.4093	0.40798	0.00141

Table 5 shows, based on the prediction bus no 4 under line outage no 17 has a maximum value.

Critical Bus Ranking through VCPI under system loading condition for Contingency case

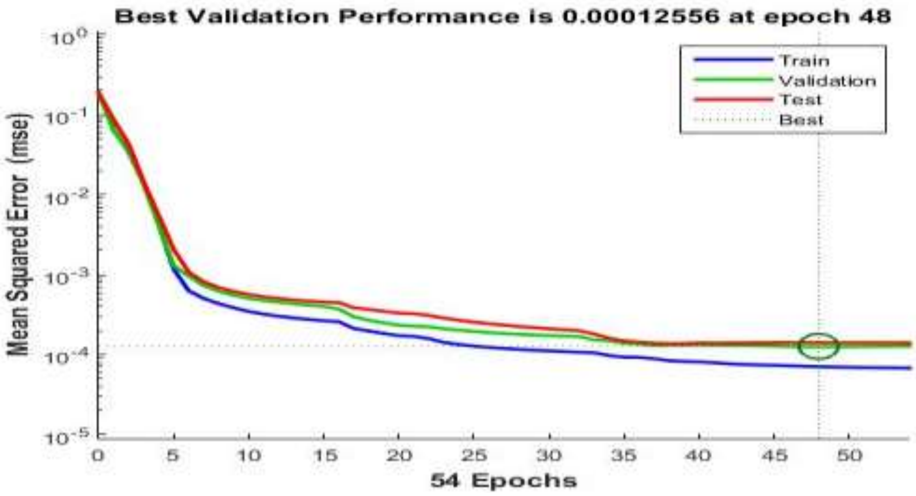

Figure 6. Performance of ANN for IEEE-14 Bus System Under Contingency Condition for VCPI

At epoch number 48 it is viewed that the best validation performance is 0.00012556 and as shown in Figure 6.

Table 6. Performance of ANN with VCPI

Actual Value	Predicted Value	Error
0.98455	0.98019	0.00436

Table 6 shows, based on the prediction bus no 9 under line outage no 1 has a maximum value.

Critical Line Ranking through L_{mn} under system loading condition for Contingency case

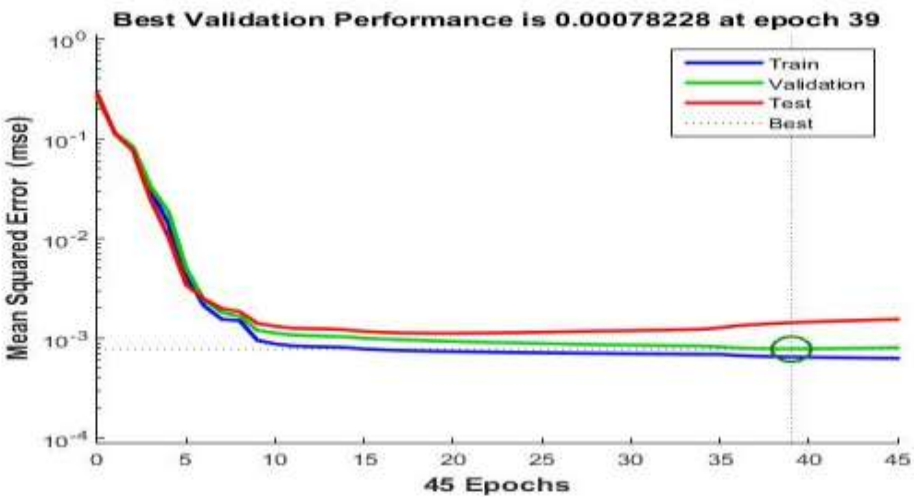

Figure 7. Performance of ANN for IEEE-14 Bus System under Contingency Condition for Lmn

At epoch number 39 it is viewed that the best validation performance is 0.00078228 and as shown in Figure 7.

Table 7. Performance of ANN with Lmn

Actual Value	Predicted Value	Error
0.50882	0.48793	0.01909

Table 7 shows, based on the prediction line no 20 under line outage no 10 has a maximum value.

10. Conclusion

In this system (IEEE-14 bus), L-Index gives all load bus voltage magnitudes and VCPI gives all bus voltage magnitudes and L_{mn} gives all line data and also these indices are used to rank the critical bus and critical branch in the system. These voltage stability indices are calculated and compare with different loading scenarios. These indices are ranging from 0 to 1, the values are nearer to 0 gives system is stable and the values are nearer 1 gives system goes critical position. Artificial neural networks reduce the computational complexity and the computational speed is a key element for online stability monitoring. The performance analysis requires previous data and it can be used to train the neural network to successfully predict voltage instability.

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