Feedforward Artificial Neural Network for Predicting Voltage Stability Indices in Power Systems

Sim Sy Yi, Goh Hui Hwang, Chua Qing Shi, Ling Chin Wan, Goh Kai Chen, Siong Kai Chien, Cham Chin Leei

Abstract*: Several electricity failures associated with the voltage stability incident have appeared in a few countries. Nowadays, main concern towards voltage stability control and prediction is no longer crucial, however significant awareness is arising to sustain power system's stability to conceal recurrence of major blackouts. Numerous types of line voltage stability indices (LVSI) being appointed to validate the weakest lines in IEEE 30-Bus test system. Besides that, LVSI is being forecasted by Feedforward Back Propagation Artificial Neural Network (FFBPNN) in order to recognize the voltage stability in IEEE 30-Bus test system. The calculated indices by using LVSI and forecasted indices by using FFBPNN are realistically applicable to discover the voltage collapse event in the system. The actual output for the VCPI(Power) in line 2-5 is 1.0459, while the predicted VCPI(Power) by using FFBPNN is 1.0459 with 3 seconds training time with 0% error percentage. Generally, the voltage collapse event has been successfully proven based on the capability of VCPI(Power). Therefore, necessary measures are capable to be performed by the power system operators to evade voltage collapse events occurred.

***Index Terms*: Feedforward back propagation neural network (FFBPNN), Line voltage stability indices (LVSI), Voltage collapse, Voltage instability, Voltage stability analysis (VSA).**

I. INTRODUCTION

Voltage instability can be classified into part of the non-linear phenomenon. The instability will be indicated whenever the maximum capability in the power network has been fully deployed. The increment and expansion of transmission network are regard as trusty concern and in combination with the latest generation facilities. However, several economic consideration and environmental concern are being contemplated, therefore these factors will lead the project to be delayed [1].

According to the theory, voltage stability is characterized from 10 seconds up to several minutes which stated by Kundur [2]. Real time monitoring must be used in the stressed power system for determining the stability so that suitable remedial actions can be taken before the occurrence of voltage instability and sooner will lead to voltage collapse.

Besides that, the notion of maximum load ability in transmission network is strongly associated with the voltage stability. Necessary actions must be implanted to decrease the stress of the transmission network whenever the utilization loading is appraising the maximum limits [3, 4].

The entire amount of generations and load arrangements, the construction of the network and the capability to access the variable resources are mainly related to the maximum loading. This is due to the maximum loading in the system is not a fixed amount [5].

The operators can perform prominent and realistic remedial actions in accordance to the available data. The purpose is for preventing the system from being inaccurate towards corrective measures and therefore will constitute to the occurrence of instability in power system. Therefore, real time security assessment and control must be implemented for conserving the safety of the system, [6].

Nowadays, assessments towards voltage stability could not be counted as part of the latest issue [7]. However due to the signification of maintaining the stability in the power system, and now they have obtained distinctive observations to prevent the repeated of major blackouts.

In order to sustain in the voltage stability area, the voltages at all buses must be preserved at balanced and adequate conditions and even after a disturbance has participated [2, 8]. A dependable power system must be always secured and exempted from any disturbances. The evaluation for the range towards voltage collapse is very significant so that compulsory exertions can be executed before the occurrence of voltage collapse [9, 10]. The main motivation for introducing voltage stability indices is to acquire the specific distance towards voltage instability in the power system [11].

Generally, voltage stability indices are segregated into two classifications. The first type is system variable based voltage stability indices and the second type is Jacobian matrix based voltage stability indices. The major concern in this paper is regards to system variable

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based voltage stability indices. The main reason is slighter calculating time is required. Moreover, it also able to accurately demonstrated the weak lines and bus for the power systems. Therefore, these are the reasons for applying system variable based voltage stability indices in this work.

A two-layer feedforward back spread neural system (FFBPNN) is picked as a component of the apparatus to prepare and approve the succession of the information. IEEE 30 transport test framework is utilized in this paper. Two units of generators, three units of synchronous condensers, 30 transports and 21 burdens are utilized in this test framework.

The rest of this paper was organized as follows. The implementation of voltage stability indices and the details of the training process for FFBPNN will be covered in the section 2. In the meanwhile, section 3 is comprised with results and discussion. Lastly, section 4 is layout with the conclusion for this paper.

II. LITERATURE REVIEW

A. Voltage Stability

The power system's capability is to preserve stable voltages at every bus despite exposed to disruptions from particular commencing state. In order to maintain the balance voltage, a power system must be able to sustain or reinstate equality for demand and supply loads [2, 12]. Besides that, voltage instable will happens once at least one bus in the system is encountering decreasing in voltage magnitude once the injection of reactive power keeps increasing [13].

Consistent drop or emerge of voltages at certain transport ready to be seen during the voltage insecurity emerging. A few factors, for example, load misfortune in some zone or stumbling of transmission lines and different parts of the security frameworks that comprise to the voltage precariousness. Certain generators that loss of synchronization will cause blackouts too [14]. At whatever point the power framework lack of the capacity to move a broad measure of electrical capacity to the heaps, at that point voltage insecurity will exhibit. Voltage decrement will start when the heap requests continue expanding [12].

Voltage breakdown is the occasion when joined by voltage precariousness prompts a power outage or unusually low voltage in a critical piece of the power framework [2, 16]. Due to the blend of occasions and framework conditions, the extra receptive power request may cause a voltage breakdown, causing a noteworthy breakdown of part of the considerable number of frameworks.

B. Voltage Stability Indices (VSI)

Voltage steadiness records are exceptionally helpful in deciding the voltage soundness of the power framework. Voltage solidness files are the scalar extents that are being utilized to watch the progressions of the parameters in the framework. Other than that, the files are likewise used to measure the separation of the specific working point with the purpose of voltage breakdown [17].

The principle goal of this subsection is to give a total and wide perspective of the voltage dependability records. As per the articles in [18, 19], the writers referenced that voltage dependability lists especially could be subdivided into two sections, which are Jacobian network based voltage strength records and framework factors based voltage steadiness files.

Jacobian grid based voltage strength records can ascertain the voltage breakdown point or greatest burden capacity of the framework and find the voltage steadiness edge. Be that as it may, these records required high computational time and for this specific reason, the Jacobian grid based voltage dependability lists are not proper for online evaluation. Framework factors based voltage security files required less computational time. The reasons are because of the framework variable based voltage steadiness files that utilized the components of the permission lattice and some framework factors, for example, transport voltages or power move through the lines. With the advantage of less computational time, framework factors based voltage security lists are reasonable to be actualized on the online evaluation and checking purposes. In the meantime, framework factors based voltage soundness lists can't proficiently appraise the edge on the grounds that their obligations are more to decide the basic lines and transports.

C. Feedforward Artificial Neural Network

ANN mimics the human mind natural sensory system [20]. There are five components in a counterfeit neuron, for example inputs, loads, summing capacity, actuation capacity and yield. Each capacity of the ANN component impersonates the four significant natural tasks of the human cerebrum (neural connections, dendrites, cell body and axon). These activities got information signal from different neurons, join them, execute the data procedure and produce a yield result.

A multilayer perceptron (MLP) is a feedforward arrange where the neurons are composed in layers. The principle normal for this kind of systems is that there are no associations between the neurons in a similar layer. The ANN comprises of an info layer, concealed layers and a yield layer of neurons. A circle speaks to a neuron while the line between two neurons speaks to the weight connections. The yield layer is contrasted with an objective and the blunder is connected in a backpropagation procedure to modify the weight [21, 22].

Additionally, ANN was presented in taking care of a great deal of issues identified with, design acknowledgment, prescription, military frameworks, monetary frameworks, arranging, expectation, order, control and ID, computerized reasoning, control frameworks and human variables [23].

This is because of their high capacity to gain as a matter of fact so as to improve their exhibition and to adjust to changes in nature notwithstanding their capacity to manage deficient data or boisterous information and can be exceptionally viable, particularly in circumstances where it is difficult to characterize the guidelines or steps that lead to the arrangement of an issue.

Feedforward ANNs allow the signal and information to travel one way only, from input through the hidden layers to output [23]. The output of any layer does not affect the same layer and therefore, there are no feedbacks, cycle or loops in this system. Inputs are associated with outputs in the feedforward ANNs which are also called as straight forward networks. This is very useful in pattern recognition.

III. METHODOLOGY

A. Line Voltage Stability Indices (LVSI)

In this examination, six distinct sorts of line voltage stability indices are being actualized. They are line stability index (Lmn), line stability factor (LQP), fast voltage stability index (FVSI), voltage collapse proximity indicator VCPI(Power), voltage collapse proximity indicator VCPI(Loss), and line collapse proximity index (LCPI). The vast majority of the line stability indices are figured dependent on the power transmission idea in a solitary line. A solitary line in a transmission system is being embodied in Fig.1.

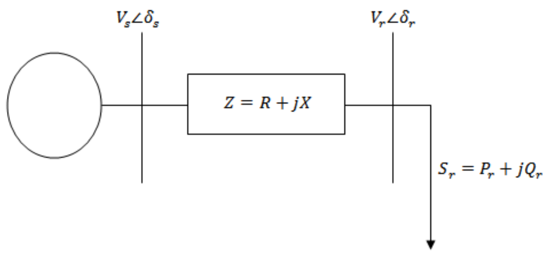

Fig.1: 2 Bus system

Where:
V_s and V_r are the sending end and receiving end voltages respectively.
δ_s and δ_r are the phase angle at the sending and receiving buses.
Z is the line impedance.
R is the line resistance.
X is the line reactance.
θ is the line impedance angle.
P_r is the active power at the receiving end.
Q_r is the reactive power at the receiving end.

B. Line Stability Index (Lmn)

Lmn index is derived by Moghavvemi and Omar in 1998 [24] based on the conceptual of power flow through a single line. The Eq. 1 can be achieved by the power flow equation.

$$Lmn = \frac{4XQ_r}{\left[V_s \sin(\theta - \delta)\right]^2} \leq 1 \qquad (1)$$

Where:
X is the line reactance.
Q_r is the reactive power at the receiving end.
V_s is the sending end voltage.
θ is the line impedance angle.
δ is the angle difference between the δ_s and δ_r.
δ_s is the phase angle at the sending bus.
δ_r is the phase angle at the receiving bus.

C. Line Stability Factor (LQP)

The LQP index is obtained by Mohamed et al. [25] using the same concept with line stability index. Therefore, the LQP index is provided in Eq. 2.

$$LQP = 4\left[\left(\frac{X}{V_s^2}\right)\left(\frac{X}{V_s^2}P_s^2 + Q_r\right)\right] \qquad (2)$$

Where:
X is the line reactance.
V_s is the sending end voltage.
P_s is the sending end active power.
Q_r is the receiving end reactive power.

D. Fast Voltage Stability Index (FVSI)

FVSI index is achieved by Musirin and Rahman [26]. Hence, the FVSI index is listed in Eq. 3.

$$FVSI = \frac{4Z^2Q_r}{V_s^2X} \qquad (3)$$

Where:
Z is the line impedance.
Q_r is the receiving end reactive power.
V_s is the sending end voltage.
X is the line reactance.

E. Voltage Collapse Proximity Indicators (VCPI)

The voltage collapse proximity indicators (VCPI) are proposed by Moghavvemi and Faruque [27] based on the maximum power transferred through a line in the power network. VCPI(Power) and VCPI(Loss) indices are listed in Eq. 4 and Eq. 5 consequently.

$$VCPI(Power)/(1) = \frac{P_r}{P_{r(\max)}} \ or \ \frac{Q_r}{Q_{r(\max)}} \qquad (4)$$

Where:
P_r is the receiving end active power.

$$P_{r(\max)} = \frac{V_s^2}{Z}\frac{\cos\phi}{4\cos^2\frac{(\theta-\phi)}{2}}.$$

Q_r is the receiving end reactive power.

$$Q_{r(\max)} = \frac{V_s^2}{Z}\frac{\sin\phi}{4\cos^2\frac{(\theta-\phi)}{2}}.$$

V_s is the sending end voltage.

$$\phi = \tan^{-1}\left(\frac{Q_r}{P_r}\right).$$

$$\cos^2\left(\frac{\theta-\phi}{2}\right) = \frac{1}{2} + \frac{1}{2}\cos(\theta-\phi).$$

Z is the line impedance.
θ is the line impedance angle.

$$VCPI(Loss)/(3) = \frac{P_{loss}}{P_{loss(\max)}} \ or \ \frac{Q_{loss}}{Q_{loss(\max)}} \qquad (5)$$

Where:
P_{loss} is the active power loss in the line.

$$P_{loss(\max)} = \frac{V_s^{\,2}}{Z}\frac{\cos\theta}{4\cos^2\dfrac{(\theta-\phi)}{2}}.$$

Q_{loss} is the active power loss in the line.

$$Q_{l(\max)} = \frac{V_s^{\,2}}{Z}\frac{\sin\theta}{4\cos^2\dfrac{(\theta-\phi)}{2}}.$$

V_s is the sending end voltage.
θ is the line impedance angle.

$$\cos^2\left(\frac{\theta-\phi}{2}\right) = \frac{1}{2} + \frac{1}{2}\cos(\theta-\phi).$$

Z is the line impedance.

F. Line Collapse Proximity Index (LCPI)

The LCPI index is based on the derivation of ABCD parameters in transmission line by Tiwari et al. [28] and is provided in Eq. 6.

$$LCPI = \frac{4A\cos\alpha\left(P_r B\cos\beta + Q_r B\sin\beta\right)}{(V_s\cos\delta)^2} \qquad (6)$$

Where:
A, B, C and D are recognised as the transmission parameters of two port network.

$A = (1+Z*Y/2)$.

$B = Z$.

$C = Y*(1+Z*Y/4)$.

$D = A$.

Z is the line impedance.
Y is the line charging admittance.

G. Feedforward Backpropagation Neural Network (FFBPNN)

Neural systems are utilized to display complex connections among sources of info and yields or to discover designs in information. In this paper, FFBPNN is utilized to discover the examples and condition from the information. It is a structure (arrange) made out of various interconnected units (counterfeit neurons).

There are six steps involved during training process for line voltage stability indices data. The steps are; loading the data, normalized, create net, setup the division, train the line voltage stability indices data using generated net, check data validation, check the performance, plot training result and show the comparison between the predictions output and the actual targets. From the prediction data and actual targets, the accuracy and precision of the neural network can be determined. Finally, the algebraic equations for the ANN model can be deduced. The flow chart for FFBPNN algorithm is illustrated in Fig. 2.

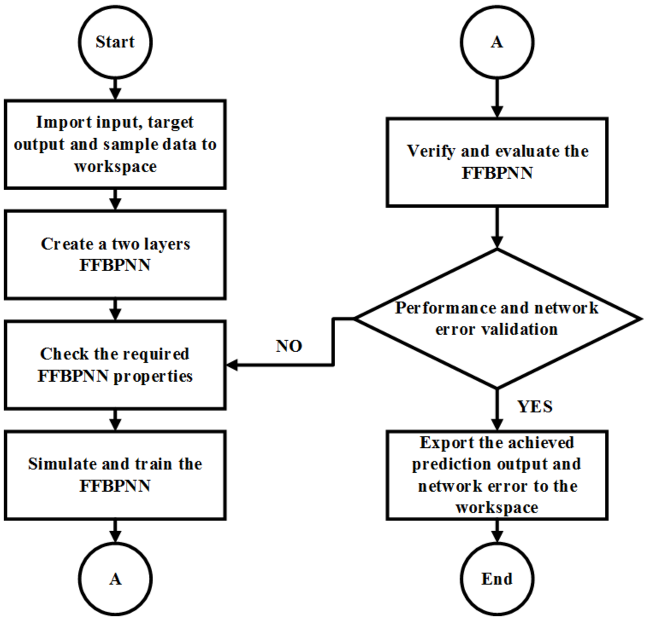

Fig.2: The flow chart for the FFBPNN algorithm

H. IEEE 30-Bus Test System

This paper essentially centered around the IEEE test framework. IEEE experiments had been generally actualized by the specialists in light of the fact that these experiments depend on the real information as per the IEEE standard power framework test framework setup.

The chose test framework is IEEE 30-bus. This test framework speaks to a segment of the American Electric Power System (in the Midwestern US). IEEE 30-bus system comprises of two generators, four synchronous condensers, 30 bus and 21 loads. The wiring graph for IEEE 30-transport framework is delineated in Fig. 3.

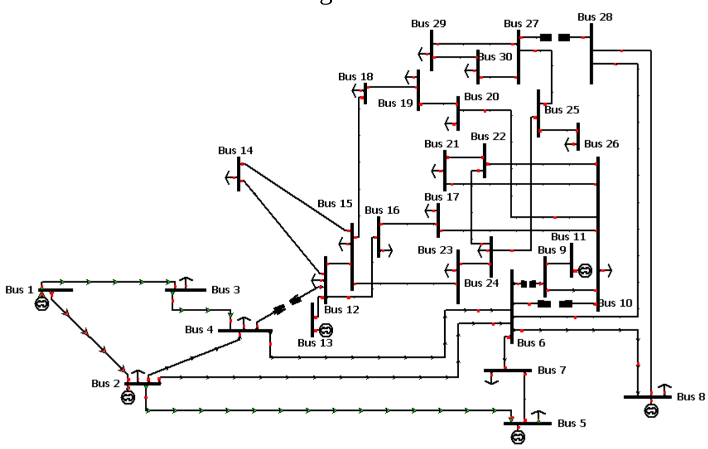

Fig.3: IEEE 30-Bus System

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IV. RESULT AND DISCUSSION

This section will mostly discuss about the utilization of ANN in this paper. A two layers feedforward back propagation technique has been actualized in anticipating the line voltage security lists esteems for the most basic line in the frameworks. This sort of system is reasonable for multidimensional mapping issues haphazardly by giving dependable information and adequate neurons in its concealed layer. From the neural system tool stash in MATLAB, the square outline of the direct layer system has been acquired as appeared in Fig. 4. The FFBPNN design comprises of an information layer, two concealed layers with two sigmoid enactment capacities and a yield layer. The system gets 4 input information and the subtleties for the info parameters can be alluded to Eq. 3 so as to assess the FVSI record. Other than that, 10 shrouded neurons are being chosen in the concealed layer and 1 shrouded neuron is being picked in the yield layer. After the preparation procedure, 1 yield information which is the evaluated FVSI list will be acquired.

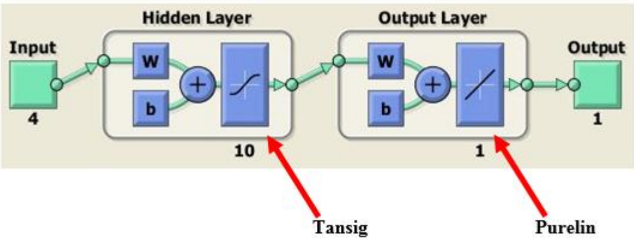

Fig.4: The flow chart for the FFBPNN algorithm for estimating FVSI index

The information layer comprises of source hubs equivalent the quantity of info signals while the yield layer comprises of hubs with equivalent number of yield signals. The information is parceled into preparing, approval and test subsets. The subset of the info estimated information (preparing set) is utilized to prepare by the system by utilizing back spread calculation. This task of the system configuration is known as learning. In the in the interim, the preparation subset is executed to perceive the ideal loads and the predisposition with the back propagation calculation of the FFBPNN organize [29, 30]. Levenberg-Marquardt calculation is executed as a numerical apparatus to limit the mistake during the preparation.

The exhibition of the FFBPNN system is approved and tried with the approval and test subsets information. The information signals from approval and test subsets are introduced to the system while the yield of the system is contrasted and the real determined yield. The approval subset is utilized to perceive the ideal number of shrouded units or to decide the venturing point for the numerical apparatus while the test subset is utilized to estimate the mistake rate of the picked last model [31].

Sigmoid initiation capacity, for example, "Tansig" enactment capacity is utilized at information shrouded layer though "Purelin" actuation capacity is utilized at concealed yield layer as outlined in Fig. 4. The "Tansig" and "Purelin" enactment capacity are chosen because of the negligible mean square mistake (MSE) acquired from the system structure. The best MLP model lies on picking the best actuation capacity and number of neurons in the concealed layer. Experimentation technique is utilized to decide the consequences of a reasonable number of neuron in each model.

The neural network layout with linear layer and two hidden layer, "w" stands for the weight while the "b" stands for the bias. The network error for ANN can be determined by using Eq. 7.

$$\text{Network Error} = \text{Actual Output} - \text{Prediction Output} \tag{7}$$

The error percentage can be calculated by using Eq. 8.

$$\text{Error Percentage (\%)} = \frac{\text{Network Error}}{\text{Actual Output}} x\ 100\% \tag{8}$$

As the system is set up to be prepared, the system loads and one-sided is first to be instated. In this paper, there are six types of line voltage stability indices and every one of the indices comprises of the distinctive number of sources of info however with one general yield. The subtleties of the contributions for the files are outlined in Table 1. The parameters in each list can be found in Eq. 1 to Eq. 6. The determined record information is separated into preparing, approval and test subsets as 60% of the information is apportioned for preparing set, 20% of the information is taken for approval set and 20% of the information is taken for test set. The weight and predispositions of the FFBPNN system are iteratively balanced through the preparation procedure as to limit the system yield estimation blunder. The blunder rate in Eq. 8 is significant as it will decide the precision of the FFBPNN model when managing foreseeing the lists in this paper.

The number of inputs for different line voltage stability indices are provided in Table 1.

Table.1: Number of inputs for line voltage stability indices

Index	Number of inputs
Lmn	6
FVSI	4
LQP	4
VCPI (Power)	5
VCPI (Loss)	5
LCPI	9

A. Prediction of Most Critical Line in IEEE 30-Bus Test System

The outcomes showed that line 2 – 5 are the most basic line at 255 seconds. Along these lines, the forecast is predominantly centered on the most basic line by utilizing the artificial neural system model.

The blue bar in Fig. 5 speaks to the genuine yield for the line voltage solidness lists while the red bar demonstrates the anticipated line voltage strength lists by utilizing fake neural system. It tends to be seen from the figure, the pattern of the anticipated yield esteems is practically indistinguishable with the first determined qualities. As it tends to be seen, the mistakes found were not critical and there is just a minor contrast between the two information esteems in the figure which is satisfactory. By and large, the determined and the anticipated qualities are comparable and this demonstrated counterfeit neural system is likewise adequate to be utilized for voltage strength observing reason.

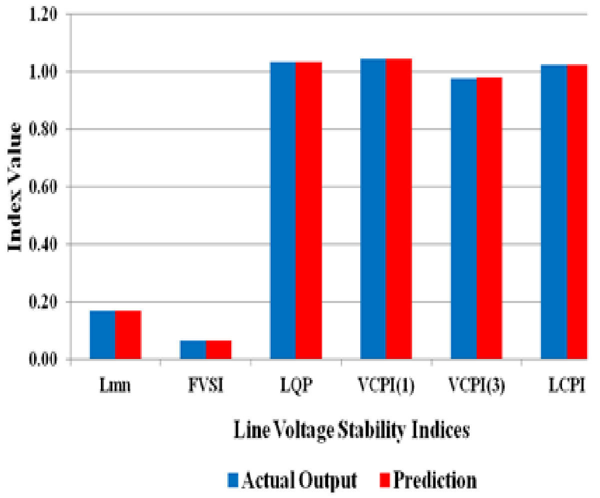

Fig.5: The examination between the real and the anticipated line voltage dependability lists (in light of line 2 – 5 at 255 seconds in IEEE 30-Bus test framework)

The rundowns for the line stability indices dependent on line 2 – 5 at 255 seconds are introduced in Table 2. The principal segment of the table demonstrates the sorts of index. Section two demonstrated the real yield esteems for the records dependent on the computation. Segment three demonstrated the forecast yield esteems from the counterfeit neural system model. Segment four and five demonstrated the system mistake and blunder rate separately. The expectation times for ANN are given in section six.

When all is said in done, the expectation yields that appeared Table 2 are comparable with the real yield and this indeed shown artificial neural system is adequate to be utilized for voltage steadiness evaluation reason.

Besides that, VCPI(Power) index showed the highest value for the actual output and prediction output among the other indices. In addition, the system blunder and mistake rate for VCPI(Power) are zero and this shown the FFBPNN forecast strategy is pertinent for voltage security appraisal reason. The FFBPNN training time for VCPI(Power) is 3 seconds.

In view of the examination, the vast majority of the indices simply contemplated of one sort of intensity at the less than desirable stopping point, either active power or reactive power.

However, VCPI(Power) considered the active power and reactive power at the receiving end of the line. For example, the line that connected to the synchronous condenser just consists of reactive power flow and does not consist of active power flow.

Table.2: Details for line voltage stability indices based on line 2-5 at 255 seconds in IEEE 30-Bus Test System

Index	Calculated Output	Predicted Output	Network Error	Error Percentage (%)	Training Time(sec)
Lmn	0.168238	0.168200	0.000038	0.022311	3
FVSI	0.066814	0.066800	0.000014	0.021285	2
LQP	1.034800	1.034800	0.000000	0.000000	2
VCPI (Power)	1.045900	1.045900	0.000000	0.000000	3
VCPI (Loss)	0.976900	0.980137	0.003237	0.331336	2
LCPI	1.024516	1.024500	0.000016	0.001548	4

For IEEE 30-Bus test system, line 2 – 5 is taken as the most critical line. The importance of determining these critical lines in the system is to function as early warning and monitoring purposes for the power system operators. Furthermore, ANN is used to forecast the most critical lines in IEEE 30-Bus power system test network. The outcomes demonstrated that the actualized ANN model is characteristic in gauging the event of framework breakdown and thus reasonable aversion move can be made previously to keep away from voltage breakdown. Overall, the network error and error percentage for VCPI(Power) provided by the ANN are zero and these results are equivalent with the ANN theoretical background. Once again, this proven that two layers FFBPNN is sufficient to forecast the line voltage stability indices.

V. CONCLUSION

Six different line voltage stability indices which are Lmn, LQP, FVSI, VCPI(Power), VCPI(Loss) and LCPI are successfully tested on IEEE 30-Bus system.

As far as general execution, whole lists are intelligent with the hypothetical foundation. At the point when the framework is steady, the line stability indices will show the incentive underneath one and cross one when the framework confronting voltage breakdown.

From this, VCPI(Power) record can recognize the voltage breakdown indicate correctly due its exactness. This index effectively demonstrated its capacity to figure the voltage breakdown point either in little or a bigger power framework organize.

In addition, a two-layer FFBPNN is utilized to foresee the most basic line in the power framework dependent on the line voltage stability indices appraisal. The outcomes demonstrated FFBPNN model is characteristic in gauging the event of framework breakdown.

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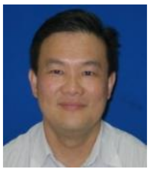

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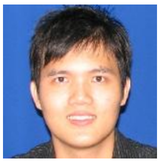

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