“Voltage Stability Analysis in Power Systems”

Ph.D. Synopsis

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By

Jyoti Iyer

(Enrollment No. 139997109003)

Supervisor:

Dr. Bhavik N. Suthar

Professor, Electrical Engineering,

Government Engineering College, Bhuj,

Gujarat, INDIA.

CONTENTS

1. ABSTRACT

- To carry out voltage stability analysis of a power system by finding the proximity of the system to voltage collapse.
- Voltage Collapse Proximity indicators, namely Line Stability Index (LSI), Fast Voltage Stability Index (FVSI), Line Stability Factor (LQP) and Novel Voltage Stability Index(NLSI) have been found and their performances have been analyzed for active and reactive load changes for IEEE 14 bus system
- The continuation power flow (CPF) method has been implemented on a two bus system. It aids in plotting the P-V and Q-V Curve on a bus so as to find the loading margins and maximum load ability. The limitation of this method has also been identified.
- The contour evaluation program gives the global response of a power system for variations in the node constraints and has been applied to a two bus system and IEEE 14 bus system for finding relationships between any two node variables with different constraints and some of the relationships between variables have been plotted.
- The Artificial Neural Network (ANN) method is proposed for online voltage stability assessment for IEEE 14 bus system with novel input- output combination.
- The efficiency and speed of the ANN has been improved by reducing the input data dimension by application of Principal Component Analysis (PCA) method for the IEEE 14 bus and IEEE 30 bus system.
- Events which produce a similar impact on the power system from voltage stability point of view have been identified.

2. STATE OF ART OF THE RESEARCH TOPIC

With the restructuring of power systems and incorporation of renewable energy sources, maintaining voltage stability of the power systems has become a matter of concern [1-4].A number of voltage collapse proximity indices have been proposed by [10-21]. These indices give information about the critical lines in the system. But these indices are non-linear.

The Continuation power flow method as reported in [22-30] helps plot the P-V and Q-V curves and hence the active and reactive power loading margin at a bus can be found. But this method does not give us the relationship between any two variables with respect to independent node parameters. Also, it is computationally expensive. The contour evaluation program [31], [34-35] provides a global response of the power system to variations in the node constraints. It facilitates generation of curves that show the system performance during disturbances and the system voltage stability limits. But this method is computationally ineffective for real time applications.

The Artificial Neural Networks (ANN) have the ability to learn complex non-linear relationships and their structures with high computational rates [7]. Many ANN based methods for online voltage stability assessment have been reported [36-49]. But the selection of inputs and number of inputs as well as the selection of the outputs is different in different papers [40-49]. Dimension reduction is done using Principal Component Analysis (PCA) in [43], [46] for various input output combinations to be presented to the ANN. Dimension reduction is also reported in [48] using Gram–Schmidt orthogonalization. The bus voltage magnitude V and phase angle δ have been used as the input to the ANN with the active power loading margin as the output by [49].

This work has taken bus voltage magnitude V and phase angle δ as the input to the ANN. The reactive power loading margin on the load buses is the output. Reduction in the input data dimension without sacrificing much of the information contained in the original data set has been done using Principal Component Analysis (PCA). The application of PCA for voltage stability assessment for identification of similar events in the power system from voltage stability point of view is the main contribution of this work.

3. DEFINITION OF THE PROBLEM AND ORIGINAL CONTRIBUTION BY THE THESIS

The increased complexities in operation and structure of the interconnected power grid has led to modern power systems facing many technical challenges [1-4]. Need for augmentation of the existing infrastructure such as lack of generation and transmission capacity, is not met due to economic and environmental constraints. This has forced the power systems to operate close to their stability limits. Additionally, the situation is found to become worse when the system operation is disturbed by grave network contingencies like tripping of heavily loaded transmission lines or large generating units. This could lead to voltage instability and make the system vulnerable to voltage collapse [1-4].

Voltage stability is the ability of a power system to maintain steady acceptable voltages at all the buses in the system when subjected to a disturbance from a given initial operating point [2-3]. The disturbance may cause the system to move into the voltage instability region. The main contributors of voltage instability are the inability on part of the network to meet the reactive power demand, insufficient reactive power generation, action of voltage control devices, sudden outages of lines and generating units and the large reactive power losses [2-3],[6]. Disturbance in the system may result in a progressive fall of the bus voltage magnitudes; but these magnitudes lie in a permissible range. Suddenly, a sharp rapid decline in the bus voltage occurs resulting in a voltage collapse. There is no warning before this sharp decline in the voltage [48]. The power system utilities should have knowledge about the voltage stability margin, which in turn acts as a caution signal to voltage collapse. This would enable the power systems to be operated with maximum security and reliability.

So, quantification of the distance from the current operating point to the voltage collapse point will serve as an early warning to any critical situation [34].

To cater to the same, a number of researchers have attempted finding the voltage stability margins using ANN [40-48]. They have used combinations of the injected real power, injected reactive power, voltage magnitude, real/reactive power of the generators, reactive power reserve of the generators, real/reactive power of the loads, active and reactive power flows in all the lines as the input variables to the ANN. The output is either an energy margin, a stability index or the active power loading margin. The bus voltage magnitude V and the phase angle δ have been used as the input to the ANN in [49] with the active power loading margin as the output.

This thesis proposes using the bus voltage magnitude V and the phase angle δ as the input to the ANN. The Reactive power loading margin, which is one of the most important voltage collapse proximity indicator has not been addressed to, by any of the above researchers. In this work, the reactive power loading margin has been taken as the output. This margin will give the necessary warning against any loading/contingent condition. The selection of V and δ as input to the ANN may lead to a substantial increase in the number of inputs for large power systems having large number of load buses. In this case, dimensions of the input vector to the ANN would be large and the components of the vectors would be highly correlated causing redundancy. The consequence of this redundancy in the input would be to produce inappropriate ANN results. As a solution to this, a novel application of the Principal Component Analysis (PCA) method that allows transformation of the original data set by a reduced number of effective features, which still retain most of the intrinsic information contained in the original data set is used.

4. OBJECTIVES OF THIS WORK

1. To analyze available Voltage Stability Analysis methods.
2. To find better Voltage Collapse Proximity indicators.
3. To use a versatile method for finding the Voltage Collapse Proximity Indicators.
4. To find the feasibility of the better Voltage Collapse Proximity Indicators for online Voltage Stability Assessment.
5. Application of enhanced Artificial Intelligence based method for Voltage Stability Assessment.

5. METHODOLOGY OF RESEARCH, RESULTS/ COMPARISONS

5.1 Practicality of Voltage Stability Indices for Voltage Stability Assessment

The voltage stability indices provide information about proximity of the power system to voltage instability. They help in identifying the critical line in the system. The maximum permissible load on a bus can be found. Thus the weakest bus in the system can be identified. Four indices have been found based on the power transfer between 2 buses on a transmission line as shown in fig. 1[11-13], [18-19].

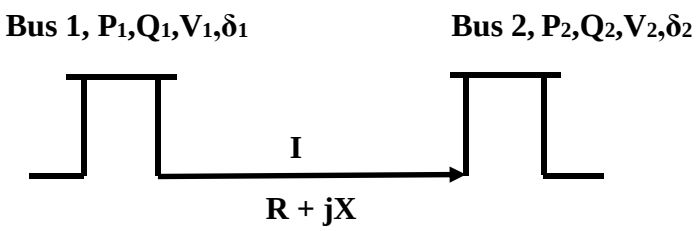

Fig. 1 Two bus System

1. Line Stability index $LSI_{ij}=\frac{4XQj}{(ViSin(\theta-\delta))^2}$

2. Fast Voltage Stability Index $FVSI_{ij} = \frac{4QjZ^2}{V_i^2\ X}$

3. Novel Line Stability Index $NLSI_{ij}=\frac{4(PjR+QjX)}{V_i^2}$

4. Line Stability Factor $LQP_{ij}= \frac{4X}{V_i^2}\left(Q_j+\frac{P_j^2\ X}{V_i^2}\right)$

Where, P_j and Q_j are active and reactive power at the receiving end,

R and X= resistance and reactance of the line, Z=impedance of the line

V_i= sending end voltage, θ= impedance angle, δ =voltage angle.

For the transmission line to be stable, $LSI_{ij}< 1$, $FVSI_{ij} <1$, $NLSI_{ij} < 1$ and $LQP_{ij} < 1$

As these indices approach 1 or become greater than 1, the line i-j becomes critical.

The load flow is run for the IEEE 14 bus system shown in the fig. 2. The results of the load flow are used to find the line indices LSI, FVSI, LQP and NLSI.

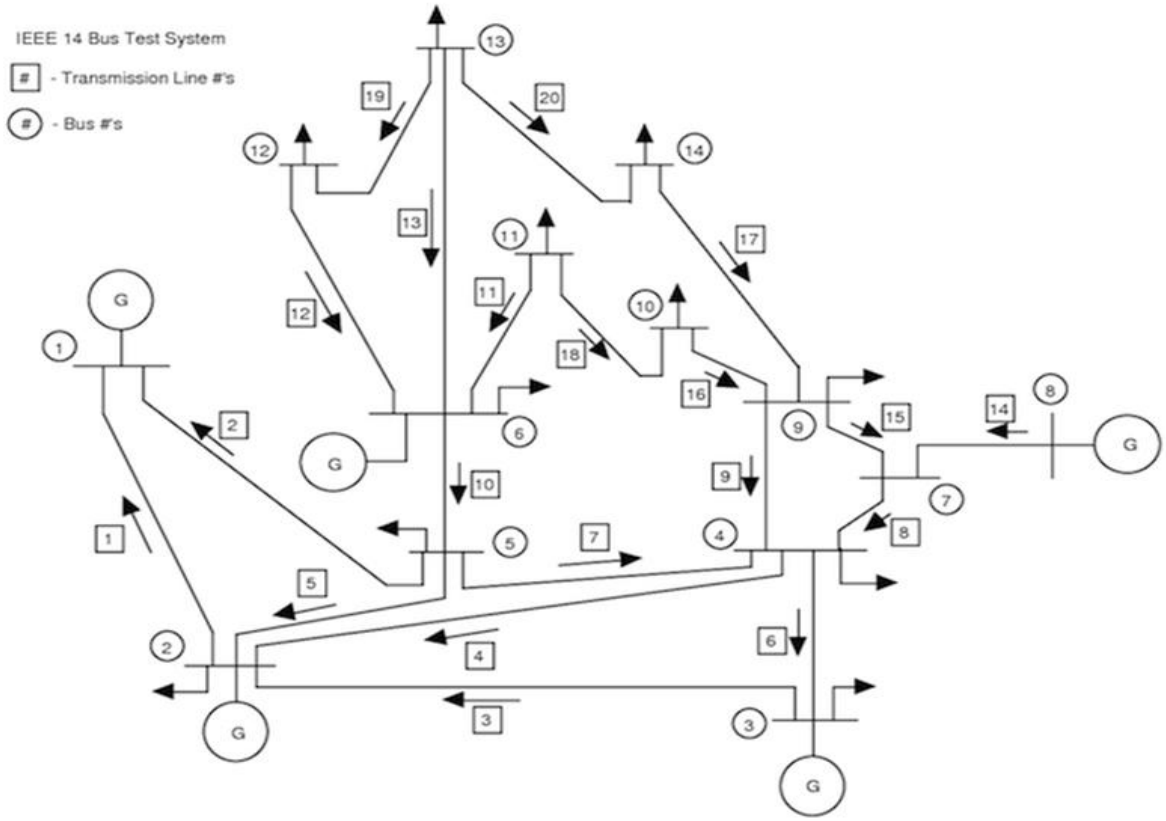

Fig. 2, Single line diagram of IEEE 14 bus system [9]

Table-1, Line Indices found for the base case for IEEE 14 bus system

Line	From bus	To bus	LSI	FVSI	LQP	NLSI
Line-1	1	2	0.4896	0.4677	0.5520	0.5504
Line-2	1	5	0.1012	0.1005	0.0944	0.0953
Line-3	**2**	**3**	**0.7980**	**0.7955**	**0.6886**	**0.6164**
Line-4	2	4	0.0102	0.0101	0.6563	0.6516
Line-5	2	5	0.1011	0.1007	0.0942	0.0957
Line-6	3	4	0.0102	0.0101	0.6106	0.6334
Line-7	4	5	0.1013	0.1008	0.0941	0.0955
Line-8	4	7	0.0002	0.0001	0.0001	0.0001
Line-9	**4**	**9**	**0.7514**	**0.750**	**0.6141**	**0.5014**
Line-10	5	6	0.3211	0.3211	0.1392	0.0957
Line-11	6	11	0.1023	0.1016	0.0541	0.0555
Line-12	6	12	0.1011	0.1007	0.0911	0.0934
Line-13	6	13	0.3148	0.3119	0.2295	0.2254
Line-14	7	8	0.0002	0.0002	0.0001	0.0001
Line-15	**7**	**9**	**0.7459**	**0.7411**	**0.6141**	**0.4095**
Line-16	9	10	0.3146	0.3122	0.2286	0.2273
Line-17	9	14	0.3105	0.310	0.3171	0.3239
Line-18	10	11	0.1231	0.1265	0.0417	0.0413
Line-19	12	13	0.3150	0.3126	0.2292	0.2257
Line-20	13	14	0.3124	0.3113	0.3146	0.3248

Table-2, Line Indices on the critical lines when Q load is increased on buses 3,9,14 by 10%

Line	From bus	To bus	LSI	FVSI	LQP	NLSI
Line-3	2	3	0.9074	0.9055	0.7432	0.6954
Line-9	4	9	0.8613	0.8502	0.6934	0.5922
Line-15	7	9	0.8432	0.8419	0.6865	0.5834

Table-3, Line Indices on critical lines when Q load is increased on buses 3,9,14 by 15%

Line	From bus	To bus	LSI	FVSI	LQP	NLSI
Line-3	2	3	1.1334	1.1376	0.8932	0.8745
Line-9	4	9	1.1141	1.1124	0.7941	0.7129
Line-15	7	9	1.1021	1.1005	0.7564	0.7334

Following the increase in the reactive load on buses 3,9,14, by 10 % and 15 %, the line indices on lines 3, 9 and 15 attained values as in the table 2 and 3 respectively. Some lines adjacent to lines 3, 9 and 15 exhibited high index values following 15% reactive load increase.

5.2 Continuous Power Flow (CPF) Method-

The conventional Newton-Raphson method fails to converge at the nose point of the P-V curve as the Jacobian becomes singular at this point. This difficulty is overcome using the CPF method which incorporates an additional unknown (also called continuation parameter, CP) and an additional equation in the basic power flow equations, which in turn ensure that the augmented Jacobian is longer singular at the nose point.

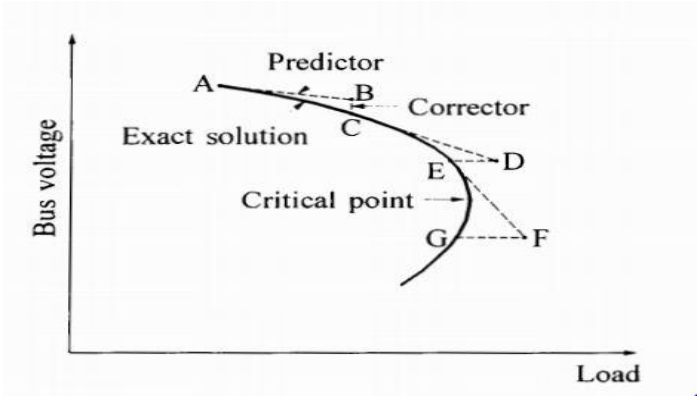

Fig. 3, A typical sequence of calculations in CPF method [4]

From a known initial solution 'A', as shown in the fig. 3, a tangent predictor estimates the predicted solution 'B' for a given pattern of load increase λ. From 'B', the corrector step then determines the exact solution 'C' [4-6], [30-31].Here, the increase in load λ is taken as the continuation parameter. The voltages for further increase in the load are predicted and corrected in the same way. A corrector step with constant λ will not converge, if the estimated

load is beyond the maximum load. For convergence, a corrector step with constant voltage is taken. So, voltage now becomes the continuation parameter.

The CPF is implemented for a 2 bus system shown in the fig. 4.

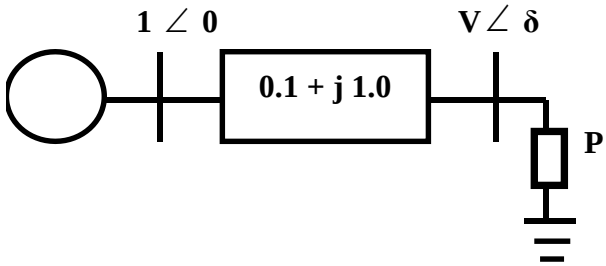

Fig. 4, Two bus System

Table-4, Results of first 4 iterations with λ as Continuation parameter (predictor step=0.1)

Iteration	δ	V	λ
1	-0.1033	0.9845	0.1
2	-0.2121	0.9567	0.2
3	-.3371	0.9109	0.3
4	-0.5070	0.8259	0.4

Between the 3rd and 4th iterations, $\frac{dV}{d\lambda}$ decreases drastically. This is an indication that we are approaching voltage stability limit point. So, CP is changed from λ to V.

Table-5, Results of iterations with V as Continuation parameter (predictor step=0.025)

Iteration	δ	V	λ
1	-0.548115	0.801800	0.416757
2	-0.588313	0.776800	0.430113
3	-0.626625	0.751800	0.439950
4	-0.663349	0.726800	0.446678
5	-0.698713	0.701800	0.450624
6	-0.732896	0.676800	**0.452056**
7	-0.766046	0.651800	0.451202
8	-0.798285	0.626800	0.448257
9	-0.829714	0.601800	0.443391
10	-0.860422	0.576800	0.436752
11	-0.890482	0.551800	0.428472
12	-0.919960	0.526800	0.418672

The P-V Curve has been plotted on the load bus no. 2 as shown in the fig. 5. The maximum load on the bus and the critical voltage value have been marked as point A.

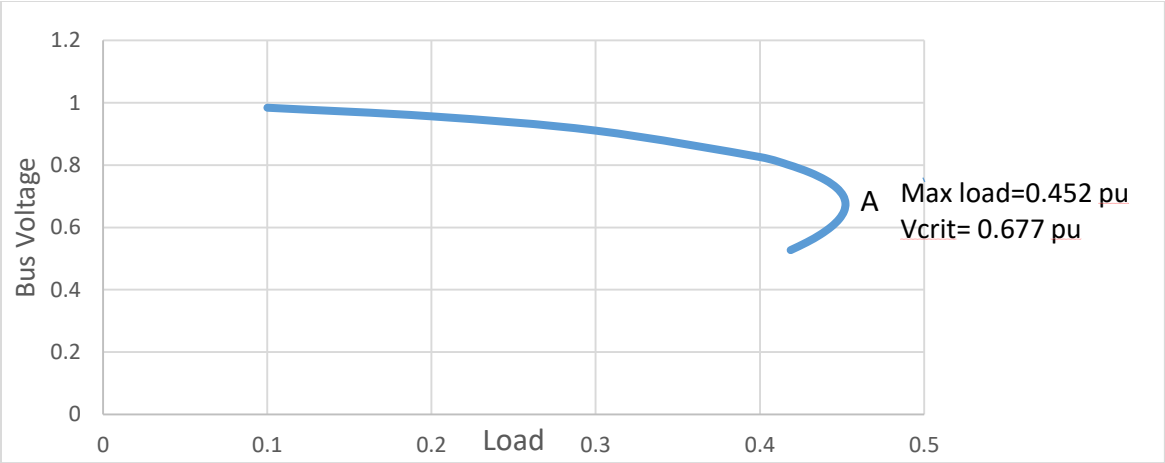

Fig. 5, P-V Curve on load bus 2

Limitations of the CPF method- This method cannot give us the relationship between any two variables with respect to independent node parameters. e.g. we cannot get the relationship between P and Q for a particular value of V, R ,X or δ. Also, the method is computationally demanding and time consuming for large power systems.

5.3 Contour Evaluation Program-

The Contour Evaluation Program gives us the relationship of specific system variables to independent node parameters [35]; which was not possible using the CPF method. The global view of the system performance to variations in the node constraints can be plotted.

The aim of this program is to calculate how any specified system quantity is related to any two independent node parameters. This relationship is visualized as a surface in three dimensions. Contour map of this surface provides useful two dimensional representation of the relationship. Any set of steady state power flow equations constitutes:

A set of 'n' non-linear constraint functions F given by F (u,k)=0

u= vector of 'n' unknowns, k = vector of 'm' knowns.

To understand the properties of this response, target functions of the type T (u,k) are defined.

The response of T (u,k) to simultaneous but independent changes in any of the two known parameters of 'k' is considered. The corresponding surface in three dimensions can be represented in two dimensions by its contour map; by curves upon which the target function T is a constant drawn in a plane of varying parameters. Each such curve is represented by equations,

F(u,x,y,k')=0 and T(u,x,y,k')=t,

where, x and y are the variable parameters of k. k' is the result of k, after removing x and y.

t is the value taken by target function T on the contour.

Table 6, Variables for contour program

Sr. No	Variable
1	Node voltage magnitude
2	Injected active power
3	Injected reactive power
4	Voltage angle of one node relative to another
5	Shunt Conductance
6	Shunt Susceptance

Table 7, Target functions for contour program

Sr. No	Target function
1	Node voltage magnitude
2	Injected active power
3	Injected reactive power
4	Voltage angle of one node relative to another
5	Total system power loss

5.3.1 Contour Program applied to 2 bus system

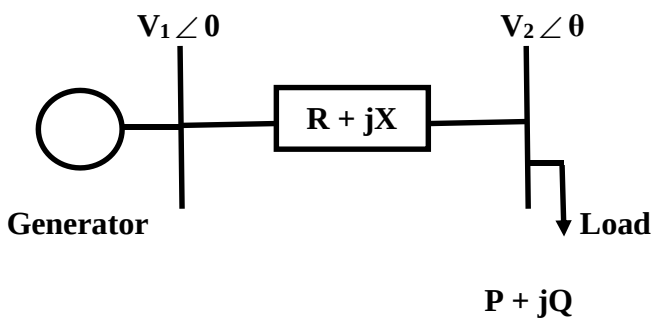

Fig. 6, Two bus system

The target function for the two bus system is

$$P^2 + Q^2 = \left(\frac{v_1 v_2}{z}\right)^2 \left(1 + \left(\frac{v_2}{v_1}\right)^2 - 2\,\frac{v_2}{v_1}\cos\theta\right)$$

Different target functions are selected and contours plotted.

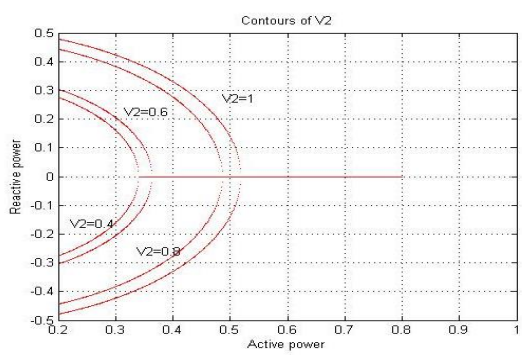

Fig. 7, P-Q curves with V as target fn.

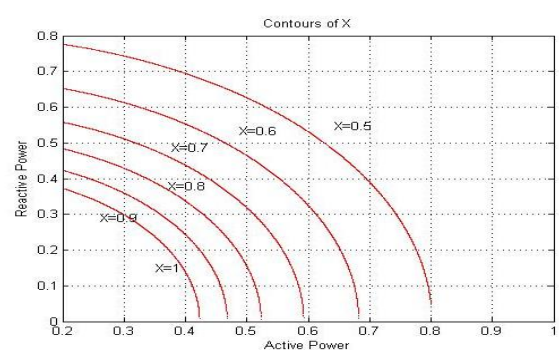

Fig. 8, P-Q curves with X as target fn.

A family of P-Q curves have been generated in fig. 7 taking receiving end voltage V_2 as the target function. It can be seen how P and Q change to keep the value of V_2 constant.

A family of P-Q curves with reactance X as the target function have been shown in fig. 8.

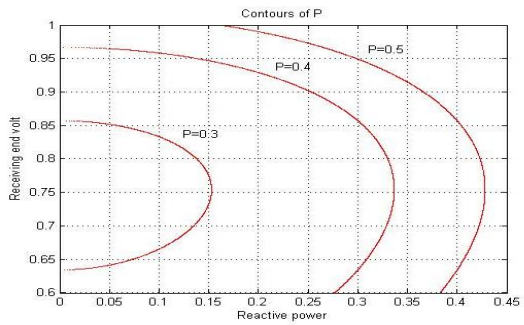

Fig. 9, Q-V curves with P as target

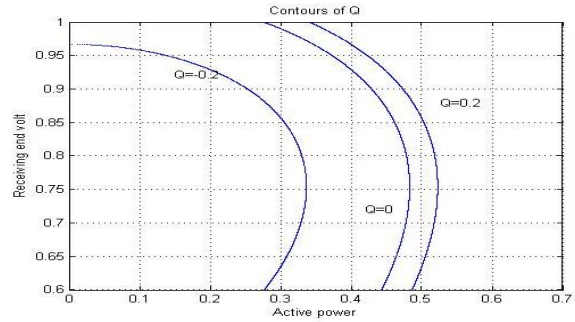

Fig. 10, P-V curves with Q as target

A family of Q-V curves with active power P as the target function and a family of P-V curves with reactive power Q as the target function have been generated in fig. 9 and 10 respectively.

5.3.2 Contour Program applied to IEEE 14 bus system

Q-V Curves on buses 12, 13 and 14 for the base case have been plotted. The blue curve gives the plot when the reactive power limits (Qlimits) of the generators are not taken into consideration. The red curve gives the plot when the generator Qlimits are taken into consideration.

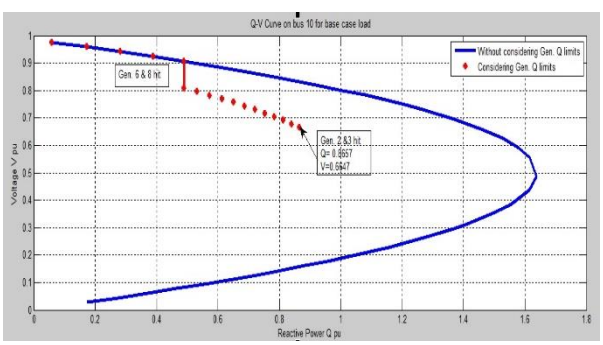

Fig. 11, Q-V Curve on bus 12 for base case

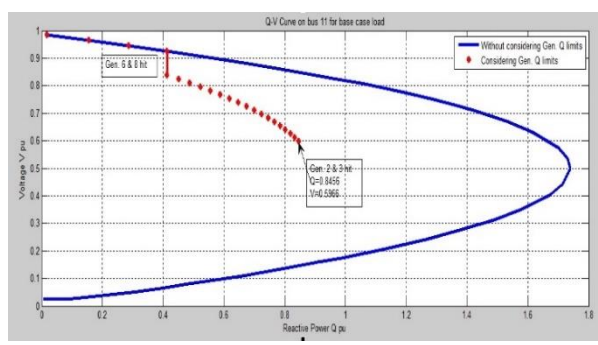

Fig.12, Q-V Curve on bus 13-base case

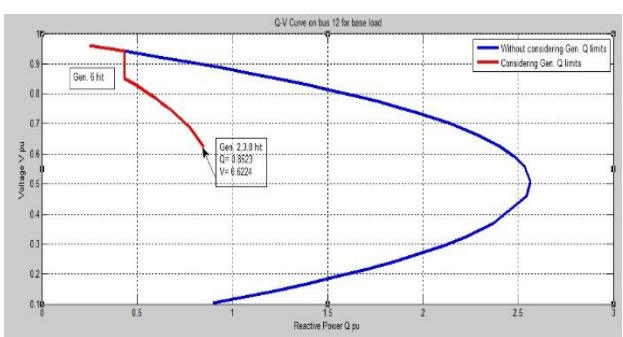

Fig. 13, Q-V Curve on bus 14 -base case

Table 8, Qmargin Comparison-IEEE 14 bus

Bus	Q loading margin (pu)	Remarks
12	0.656	Close to PV bus
13	0.596	Little away from PV bus
14	0.4623	Far from PV bus

5.3.3 Q-V Curve on bus 10 with δ as target fn.

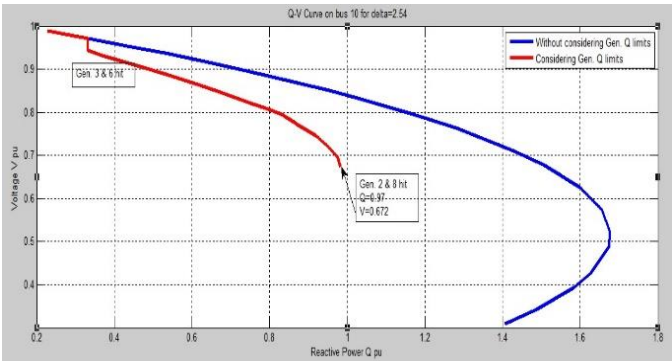

Fig.14, Q-V Curve with δ=2.54

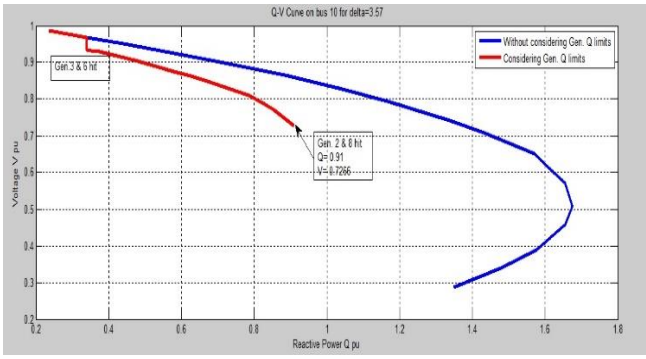

Fig.15, Q-V Curve with δ=3.57

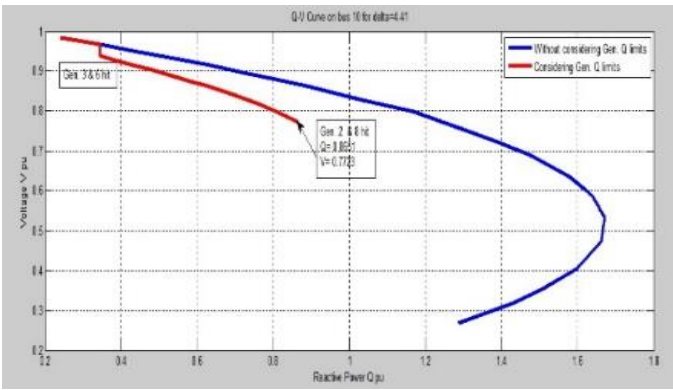

Fig. 16, Q-V Curve with δ=4.41

Table 9, Qmargin with change in δ

δ	Qmargin on bus 10
1.95	0.803
2.54	0.77
3.57	0.71
4.41	0.6651

From the table 9, it is seen that as the load angle δ increases, one of the most important VCPI, the reactive power loading margin, Qmargin decreases. The quantum of decrease in this Qmargin can be calculated using the contour program.

5.3.4 P-Q Curve on bus 9 with V as target function

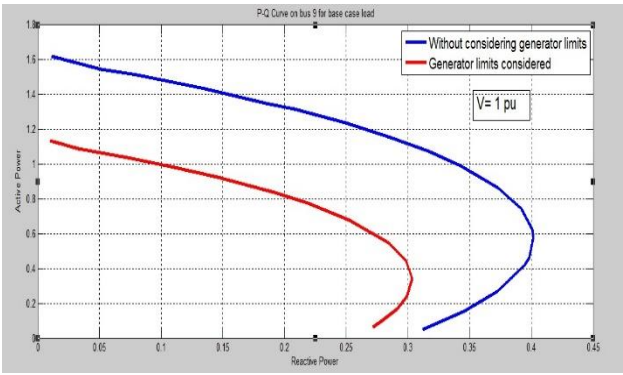

Fig. 17, P-Q Curve on bus 9 for base case

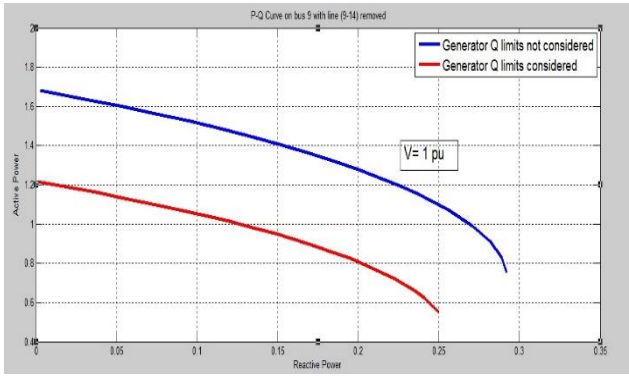

Fig. 18, P-Q on bus 9 with outage of line (9-14)

The P-Q curves are generated taking voltage V as the target function [33].These curves have been plotted on bus 9. The maximum reactive power load on bus 9 under base case and when outage of line (9-14) occurs is shown. Thereby, to keep the voltage constant at 1 pu, the value by which the reactive power load on the bus 9 needs to be changed can be found.

Table 10, Qmaximum on bus 9 under base case and contingent condition

Case	Generator Q limits not considered Qmax (pu)	Generator Q limits considered Qmax (pu)
Base	0.4018	0.3
Line (9-14) removed	0.292	0.25

The complicated behavior of a multi bus system when abnormal conditions and faults occur on it can be visualized using the contour evaluation method. This method acts as a new security operating tool for power system operation. The method, although fairly accurate, is not computationally effective for real-time application.

5.4 Application of Artificial Neural Network (ANN) for online voltage stability analysis-

The voltage stability assessment problem is non-linear in nature. The ANN approach to real time assessment and improvement of voltage stability has been proposed considering its ability to learn non-linear problems offline with selective training which allows it to interpolate unforeseen situations. They are capable of parallel data processing with high accuracy and fast response. Once trained, the execution time of the ANN's subject to any input is very less. The analytical methods of voltage stability analysis are computationally expensive. So, the ANN's have been used for online response of voltage stability with sufficient degree of accuracy [36-49]

5.4.1: Steps for using ANN for any application

1. Selection of input variables and number of input variables.
2. Selection of output variables and number of output variables.
3. Number of neurons in a hidden layer.
4. Number of hidden layers.
5. Activation functions used at the hidden and output layers for computation.
6. Training of the input patterns (about 75-80 %).
7. Testing of the remaining patterns (20 -25%).

5.4.2 Voltage Stability Assessment using ANN

1. Selection of Inputs and Output to the ANN –In this work, voltage magnitude V and phase angle δ on each load bus have been selected as the inputs to the ANN. The reactive power loading margin on each load bus has been selected as the output. This has been done for the IEEE 14 and IEEE 30 bus system.
2. Generation of input and output patterns- The IEEE 14 bus system has 9 load buses. So there will be 18 inputs in one input pattern. The output is the reactive power loading margin (Qmargin) on the load buses. The input patterns have been generated by running load flow. The output Qmargins have been found using contour program. About 250 input patterns have been generated considering various loading and contingent conditions.
3. Design and Training of the ANN for IEEE 14 and 30 bus system– The ANN is designed and trained by considering different number of hidden neurons and different activation functions at the hidden and output layer. Finally an architecture with 15 hidden neurons is found to give the best results. 80 % of the 250 samples are used for training. TANSIG transfer function is used at the hidden layer. PURELIN transfer function is used at the output layer. The training function for training the ANN is TRAINLM. The error function mean squared error (MSE) is then found.

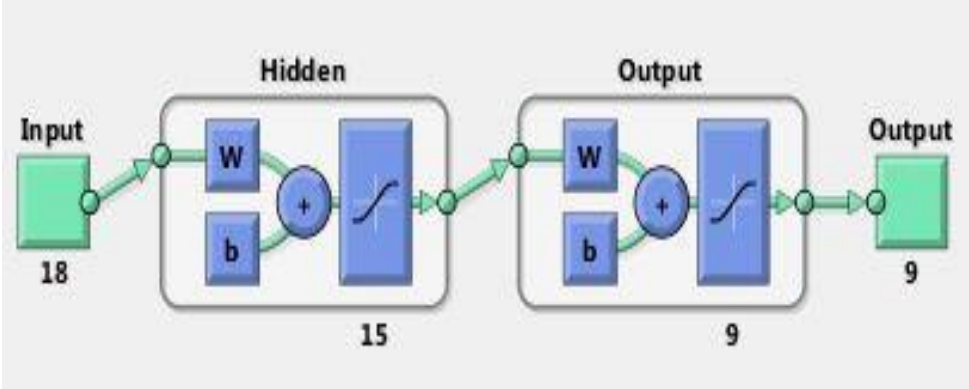

Fig. 19, Neural Network Architecture

4. Testing the ANN- Remaining 20 % of the 250 samples are used for testing of the trained ANN.

Table 11, Qmargin by ANN and analytical method Case Q_{15}bus11

(Q increase by 15 % on bus 11) for IEEE 14 bus system

Bus No	Qmargin by ANN for test case Q_{15}bus11(pu)	Qmargin found using analytical method(pu)	% Error
4	0.3125	0.31192	0.058
5	0.19269	0.19009	0.26
7	0.21531	0.21520	0.011
9	0.26827	0.26815	0.0117
10	0.1187	0.11821	0.049
11	0.04898	0.04873	0.025
12	0.061001	0.061024	0.0023
13	0.05131	0.05021	0.0113
14	0.05874	0.058726	0.0014

5.4.3ANN Implementation on IEEE 30 bus system:

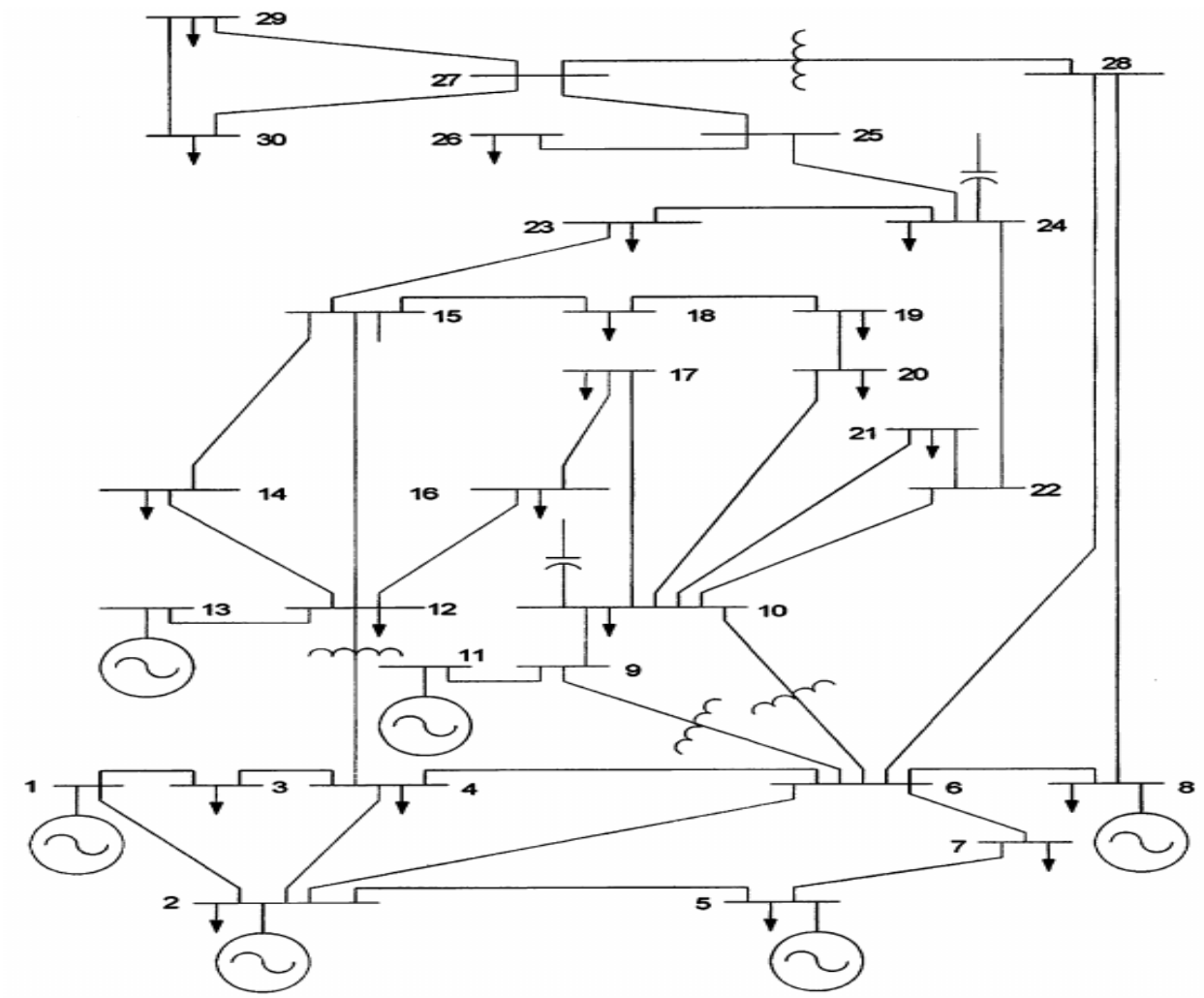

Fig. 20, Single line diagram of IEEE 30 bus system [9]

In the IEEE 30 bus system, there are 44 inputs in one pattern. The output is the Qmargin on the 22 load buses. About 650 input patterns are generated for healthy and other contingent conditions. The healthy conditions include single bus loading, multi bus loading and random loading. The contingent conditions include sudden loss of a line or loss of a generating unit. The ANN is trained with 80 % of the input sample patterns. Then testing is done from the remaining 20 % patterns.

Table 12, Qmargin by ANN and analytical method- Case Loss of line (27-30) - IEEE 30 bus system

Bus No	Qmargin(pu) by ANN Case-Loss of line (27-30)	Qmargin (pu) by Analytical method	% Error
3	0.13511	0.13514	0.003
4	0.13400	0.13403	0.003
6	0.30121	0.30125	0.004
7	0.34129	0.34132	0.003
9	0.28146	0.28144	0.002
10	0.1577	0.1573	0.04
12	0.15701	0.1570	0.001
14	0.10618	0.10613	0.005
15	0.1046	0.1041	0.05
16	0.10841	0.10834	0.007
18	0.0840	0.0837	0.03
19	0.0539	0.0535	0.04
20	0.0580	0.0577	0.03
21	0.0761	0.0758	0.03
22	0.0862	0.0856	0.06
24	0.1045	0.1048	0.03
25	0.0690	0.0672	0.18
26	0.0576	0.0568	0.08
27	0.0412	0.0385	0.27
28	0.1731	0.1701	0.3
29	0.0385	0.0305	0.8
30	0.0378	0.0352	0.26

5.4.4 Application of Principal Component Analysis for input data dimension reduction

Voltage stability is a complex problem. It cannot be modelled with the data obtained from one part of the system. The data grows with the size of the network. Also, a significant part of available variables is redundant. Most of them do not provide new information to the model. So, a method that allows the extraction of the most significant information is wanted [8].

Principal Component Analysis (PCA) method is used to reduce the dimensions of data without much loss of information. It reduces the dimensionality of a data set by finding a new set

of variables, smaller than the original set[8][50-53].It captures the big variability in the data and ignores the small variability. It retains most of the original sample's information. By information is meant, the variation present in the sample, given by the correlations between the original variables. The new variables are called principal components. They are uncorrelated and are ordered by the fraction of the total information each retains. This method presents a good data compression alternative with minimal loss of information.

5.4.5 Procedure for PCA Implementation on IEEE 14 and 30 bus system:

For IEEE 14 bus system

1. No. of training patterns, m=234 and number of inputs in one pattern=18.
   Form matrix D of size (18 x m).
2. Mean of each row of matrix D found as $D_m = \frac{1}{m}\sum_{i=1}^{i=m} x_i$
3. Mean subtracted matrix, D_{new} of size (18 x m) is found to normalize the data.
4. Covariance matrix C is found of size (m x m) = $D^T * D_{new}$.
5. Eigenvectors of the covariance matrix are found [V, E] = eig(C), where V is the (m x m) eigenvector matrix and E is the (m x m) eigenvalue diagonal matrix.
6. Feature vector F is formed by sorting the eigenvectors in the descending order. Selected eigenvectors correspond to eigenvalues in the descending order.
7. F= [eig_1, eig_2----eig_m]. Selected 9 eigenvectors/principal components.
   So, F is of size (18 x 9)
8. Final data selected for projection, G of size (9 x m) =$F^T * D_{new}$. This has given us the original data with reduced dimensions, still retaining most of the intrinsic information.

For IEEE 30 bus system

1. No. of training patterns, m=538 and number of inputs in one pattern= 44.
   Matrix D of size (44 x m) is formed.
2. No. of eigenvectors/principal components selected =21.
3. Final data selected for projection, G of size (21 x m) =$F^T * D_{new}$. This has given us the original data with the largest possible amount of information retained.

5.4.5.1 Selection of number of Principal Components (PC):

The first principal component captures maximum variance in the data set. Larger the variability captured in the first component, larger will be the information captured by it. No other component can have a variability higher than the first principal component. This component will result in an eigenvector close to the data set.

The second component captures from the remaining variance in the data set. Its co-relation with the first component is zero. Since there is no co-relation between the two components, they are orthogonal. All successive principal components capture from the remaining variance without being correlated with the previous components. A random example of the proportion of variance captured Vs. the no. of principal components has been shown in the fig. 21. It is seen that beyond the 32nd principal component, no new information is captured. So, unnecessarily we need not consider the higher principal components. It will only result in redundancy.

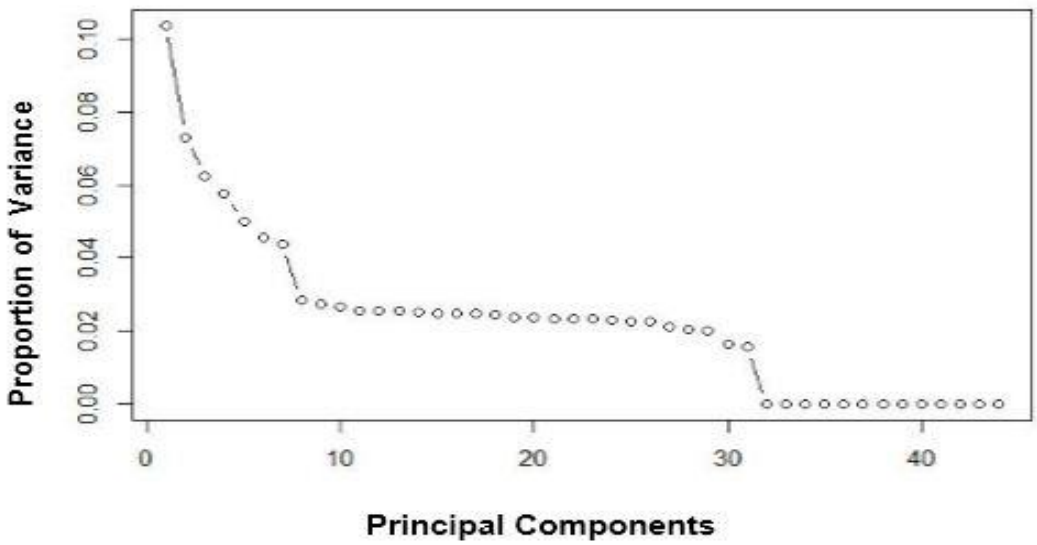

Fig. 21, Number of Principal Components V/s. Variance

Table 13, PCA Application for IEEE 14 bus system

Case P_{15}bus9 (Active load increased by 15 % on bus 9)

Bus No	Qmargin (pu) by ANN	Qmargin (pu) using PCA				% Error (PC=9 with ANN)
	P_{15}bus9	PC=6 Q_{22}bus14	PC=7 Q_{13}bus4	PC=8 Q_{20}bus10	PC=9 Q_{18}bus13	
4	0.31616	0.3170	0.3163	0.31624	0.31622	0.006
5	0.1901	0.19385	0.19321	0.19295	0.19294	0.284
7	0.2131	0.2269	0.2213	0.2174	0.2172	0.41
9	0.2332	0.2387	0.2329	0.2315	0.2313	0.19
10	0.1182	0.1194	0.1151	0.1123	0.1120	0.62
11	0.06102	0.06218	0.06213	0.0614	0.0611	0.008
12	0.0656	0.0623	0.0654	0.0642	0.0639	0.17
13	0.0536	0.0498	0.0539	0.0465	0.0462	0.74
14	0.0524	0.0481	0.0543	0.0503	0.0500	0.24

Table 14, PCA Application for IEEE 30 bus system

Case $P_3Q_3bus_{14}$ (Active and reactive load increased on bus 14 by 3% each)

Bus No	Qmargin (pu) by ANN	Qmargin (pu) using PCA				% Error PC=21 with ANN
	$P_3Q_3bus_{14}$	PC=18 Q_3bus5	PC=19 Q_5bus8	PC=20 $P_{10}bus17$	PC=21 P_7bus23	
3	0.13512	0.13519	0.13514	0.13512	0.13510	0.002
4	0.1340	0.13413	0.13402	0.13400	0.13401	0.001
6	0.30127	0.30124	0.30117	0.30120	0.30120	0.007
7	0.34129	0.34123	0.34122	0.34135	0.34134	0.007
9	0.28150	0.28148	0.28145	0.28147	0.28147	0.003
10	0.1581	0.1587	0.1582	0.1578	0.1577	0.04
12	0.1570	0.15710	0.15704	0.15695	0.15693	0.007
14	0.10618	0.10634	0.10625	0.10627	0.1062	0.002
15	0.1044	0.1057	0.1052	0.1046	0.1039	0.03
16	0.1083	0.10853	0.10851	0.10843	0.10843	0.013
18	0.0840	0.0851	0.0847	0.0843	0.0841	0.01
19	0.0542	0.0553	0.0548	0.0542	0.0542	0
20	0.0582	0.0594	0.0587	0.0579	0.0577	0.05
21	0.1921	0.1937	0.1929	0.1917	0.1916	0.05
22	0.0865	0.0876	0.0869	0.0859	0.0858	0.07
24	0.10485	0.10497	0.10491	0.10488	0.10484	0.001
25	0.0692	0.0698	0.0697	0.0693	0.0691	0.01
26	0.0584	0.0589	0.0587	0.0585	0.0584	0
27	0.0440	0.0452	0.0443	0.0439	0.0439	0.01
28	0.1821	0.1831	0.1820	0.1825	0.1825	0.04
29	0.0405	0.0413	0.0409	0.0407	0.0407	0.02
30	0.0402	0.0411	0.0403	0.0402	0.0402	0

After the application of PCA, we are able to reduce the input dimension from 18 to 9 in IEEE 14 bus system and from 44 to 21 in IEEE 30 bus system. Also, PCA helps identify similar events in a power system from voltage stability point of view.

Table 15, Similar Events in the power system w.r.t. voltage stability

System	Disturbance	Events found similar after PCA Application				Dimension Reduction after PCA
IEEE 14 bus	$P_{15}bus9$	$Q_{22}bus14$	$Q_{13}bus4$	$Q_{20}bus10$	$Q_{18}bus13$	(18 x 234) to (9 x 234)
IEEE 30 bus	P_3Q_3bus14	Q_3bus5	Q_5bus8	$P_{10}bus17$	P_7bus23	(44 x538) to (21 x 538)

6. ACHIEVEMENTS WITH RESPECT TO OBJECTIVES

- The voltage stability analysis has been carried out on the IEEE 14 bus and IEEE 30 bus system by finding VCPI using different assessment techniques.
- The voltage stability indices give us information about the critical line in a system with respect to a bus.
- The Continuation Power Flow method helps find the maximum load ability on a bus and the margin to voltage instability.
- The Contour evaluation program gives us a global view of the system performance during normal and faulty conditions. The Q-V curves give us the voltage stability margin considering various target functions. This Contour evaluation program has been found to be the best assessment method for Static Voltage Stability Assessment. It has been applied to IEEE 14 and 30 bus test systems.
- With the increase in the size of the power system, training the ANN's for all possible contingencies and loading levels becomes a tough task. So, Principal Component Analysis (PCA) is applied for reduction in the input data dimension.
- PCA results in reduction in the input data dimension, which not only curtails the computational burden and cost of future data collection of the ANN, but also results in generalized improvement in the accuracy of the ANN.
- The application of PCA helps identify similar events in the power system from voltage stability point of view; the events that produce a similar impact on the system where voltage stability is concerned.

7. CONCLUSION

This work has proposed the idea of similar events occurring in a power system from voltage stability point of view. The events which produce a similar impact on the power system where voltage stability is concerned, have been identified.

The bus voltage V and phase angle δ taken as the inputs to the ANN are the most appropriate input features. The ANN is used to estimate the reactive power loading margin under normal operating and various contingent conditions.

For large power systems having a large number of interconnecting lines, training ANN's for all credible contingencies and load levels is a demanding task.

The proposed PCA method improves the efficiency and speed of the ANN by reducing the input data dimension. In this work, the input dimension in the IEEE 14 bus and IEEE 30 bus system were initially 18 and 44 respectively. This has been reduced to 9 and 21 respectively by use of the PCA method.

Reduction in the number of ANN inputs not only reduces the computational burden and the cost of future data collection, but also improves the generalized accuracy of the trained neural networks without compromising on the high execution speed.

8. PAPERS PUBLISHED

1. Jyoti Iyer, B.N.Suthar "Evaluation of Power Flow Solution Space Boundary", 2016 IEEE International Conference on Next Generation Intelligent Systems (ICNGIS) held during Sept. 1-3, 2016 at Rajiv Gandhi Institute of Technology, Kottayam, Kerala, 978-1-5090-0870-4/16 2016 IEEE.
2. Jyoti Iyer, B.N.Suthar "Plotting of Voltage Contours in the P-Q plane using contour evaluation program" International Conference on Research and Innovations in Science, Engineering & Technology held during Feb. 17-19, 2017 at BVM Engineering College, Kalpa Publications in Engineering, Volume XXX, 2017, pp 1-8.
3. J.R. Iyer, B.N.Suthar, "A Novel Method for Power System Voltage Stability Monitoring Using Artificial Neural Networks with Reduced Input Dimension" IUP Journal of Electrical and Electronics Engineering, UGC List of Journals, Volume XI, No. 1, 2018. ISSN: 0974-1704

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