A Novel ANN Based Method for Online Voltage Stability Assessment

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Abstract: - **This paper presents an ANN based method for on-line voltage stability assessment of power systems. The most vulnerable load buses of the system from voltage stability point of view have been identified by Modal analysis. A separate feed forward type of ANN is trained for each vulnerable load bus. For each of these ANN's, some novel inputs, comprising of the moments obtained by multiplying the real power and reactive power contributions with the electrical distance between each generator-vulnerable load bus pair and the reactive power margins available at the generators, are used in addition to the usually used inputs viz. the real and reactive power loads and the voltage magnitude at the vulnerable load bus. The target output for each input pattern is obtained by computing the distance to voltage collapse from the current system operating point using a continuation power flow type algorithm (*Contour Program*) incorporating the Q limits of the generators. The proposed method has been applied to the IEEE 30 bus test system. The distances to voltage collapse obtained by the ANN and by the analytical method are found to be closely matching with each other.**

Index Terms: - **Real Time Monitoring, Voltage Stability, Artificial Neural Network,**

I. INTRODUCTION

Power system voltage instability problem has been a growing problem since the last couple of decades and is emerging as a dominant threat for secure and reliable operation of power systems. Heavy reactive power flows in long transmission lines and inadequate reactive power compensation at major load buses are the main causes of voltage instability [1]. In the restructured modern power systems, system operators are many times forced to exploit the existing capacity of the network by incorporating a large number of FACTs devices in the system. Sometimes, in such situations, the actions of the automatic protective equipment may crash the network before the operator would get the indications from the alarms in place. Therefore, it is necessary to have a fast method to evaluate static voltage stability comprehensively by examining and quantifying the production, transmission and consumption of the reactive power on a system wide basis and relate this to the voltage stability margins at the vulnerable load buses.

Various methods for voltage stability assessments of power systems have been documented in the IEEE Subcommittee report [2]. In the modal analysis method, it is difficult to account for the discontinuities that arise in the system because of the reactive power sources hitting the limits. However, the Modal analysis based methods are useful [3] for identifying the most vulnerable load buses/area in the system.

It is reported that generally the voltage instability problem is caused by system's inadequacy to meet the reactive power demands from the available reactive power sources in the system. Therefore, the QV curves drawn for different real power loadings are preferred over PV curves for voltage stability analysis [4]. The reactive power loading margins, the distances between the nose points of the QV curves drawn for the different load buses and the current operating point of the system is considered to be the most basic and widely accepted Voltage Collapse Proximity Indicator (VCPI) for the voltage stability assessment [1]. The QV curve method has been addressed by Schlueter [3] for both the "Loss of Voltage Controlled" voltage instability (caused by inadequate reactive power reserves available at the various sources) and "Clogging" voltage instability (caused by the inadequacy of the reactive power transfer capability of the transmission systems).

It is well known that a trained ANN is a very suitable tool for on-line use over the other computationally expensive methods. There have been some attempts to use ANN for online voltage stability assessment [5, 6,]. References [5] propose the energy function approach for voltage stability assessment and come out with voltage stability margin at the system level. In Ref. [6] the proposed ANN predicts L indices (which are simplified measures of maximum loadability of load buses) for all the load buses in a reduced order system. The principal objective of the present paper is to train a separate ANN for each of the vulnerable load buses of the system. We envisage that this would be an useful tool for continuously tracking the reactive power margins available for voltage instability at these buses as the system loading conditions (in terms of real power consumption and power factor variations at the various load buses) change around the peak load base conditions. In our opinion, Monitoring of real time reactive power margins will be very useful to initiate appropriate control actions to avoid any impending voltage instability situations

When an ANN-based method is to be devised for a problem the first question which arises is "what are the different principal parameters/conditions/factors which play vital role in estimating/predicting the desired output of the ANN?" On these considerations, a set of novel inputs to each of these ANN's consisting of (i) The real and reactive power

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moments obtained by taking the products of the power contributions from the various generators to a particular vulnerable load bus with the electrical distances between the generators and the corresponding load bus, (ii) Reactive power margins at the generator buses, (iii) Real and reactive power loadings at the particular load bus and (iv) Voltage magnitude at that load bus has been proposed in this paper. The training of the ANN's should be done with an exhaustive set of input-output patterns covering the realistic ranges of all the operating points and relevant system parameters discussed above. The target output selected for each of the input patterns is the distance to voltage collapse obtained using QV curves. The analytical method used in the present paper for drawing QV curves (incorporating the reactive power limits of the generators) is explained in brief in sec V.

The overall procedure involved in the design and training of the ANN's may be summarized as; (i) Generation of loading patterns (Described in Sec II), (ii) Modal analysis for each of the loading patterns (Described in Sec III), (iii) Generation of patterns (Described in Sec IV and V) and (iv) Training of the ANN's (Described in Sec. VI).

II. Generation of Loading Patterns

Starting with the base case assumed as the system peak load conditions, a set of realistic system loading patterns are generated by the following procedure: (i) Keeping the real power loading of the system constant at the peak values, and incrementing the reactive power loads at randomly selected multiple load buses till the reactive power loading at these buses become equal to the real power loadings at these buses (ii) keeping the reactive power loadings at all the load buses constant at the peak values, the real power loadings of the system are reduced in steps until the total system real power load becomes 90% of the system peak value. In these loadings the real power loading is distributed on randomly selected individual load buses prorata to their base case values and also the real power loading at any load bus is not allowed to go below reactive power loading at that load bus. (iii) Both real and reactive power loadings at all the randomly selected load buses are increased simultaneously. In this set of patterns, the system real power load is increased from 90 % values generated in (ii) to the original peak level in steps simultaneously increasing the reactive power loading for each of these patterns to the same set of values as obtained in (i).

III. Identification of Vulnerable Load Buses

It is well known that in a strongly coupled power system, as the system reactive power loading is increased, some of the load buses only will experience more dips in their voltage magnitudes depending upon their relative electrical distances with respect to the reactive power sources. The modal analysis of the reduced (corresponding to the Q-V relationship) Jacobian matrix and computation of the bus participation factors [4] will be useful for identifying the few most vulnerable buses from the voltage stability point of view. It has been reported [4] that only very few smallest eigenvalues corresponding to weak modes will play the major role in deciding the voltage stability of the system. The most vulnerable buses are to be identified for each of the loading patterns generated in Sec. II by running the modal analysis program repeatedly.

IV. Generation of Input Patterns for ANN

Generation of input patterns for each of these ANN's involves running of two computer programs, i) for computing the complex power contributions by each generator in meeting the load requirements at the particular vulnerable load bus for which the ANN is designed and ii) for computing the electrical distance between each generator and the particular load bus. The procedures used in these programs are descried in the following sub-sections. The product of the power contributions and the electrical distance corresponding to each generator-load pair may be designated as the power-electrical distance moment for this pair and the real and reactive power moments obtained for all such pairs are to be used as inputs for the ANN. In addition, the real and reactive power loads, voltage magnitude at the particular load bus and the reactive power margins available at all the generator buses corresponding to each loading pattern are also to be used as the inputs for the ANN.

A. Computation of individual generator's contribution to a load

Many references [7-9] are available in the literature, for computing the individual generators' contributions in meeting the loads at the various load buses in the system. These algorithms are very much used in the current context of restructuring of modern power systems. In this paper the algorithm proposed by John Tang [9] has been used. This algorithm essentially involves converting the loads to equivalent shunt admittances and forming the Z-bus of the network including the equivalent load admittances corresponding to a particular system operating point in the matrix. The technique used is injection of current only at one generator at a time leaving the other generators open and evaluating the power contribution by this generator in meeting the load at the particular load bus considering the impedances offered by various paths between the generator and load buses.

For the system having L_N number of total load buses and G_N number of total generator buses, using the above method the following matrix can be formed,

$$S_{CONT} = \begin{bmatrix} S_{L1G1} & S_{L1G2} & \ldots & S_{L1GN} \\ S_{L2G1} & S_{L2G2} & \ldots & S_{L2GN} \\ \ldots & \ldots & \ldots & \ldots \\ S_{LNG1} & S_{LNG2} & \ldots & S_{LNGN} \end{bmatrix} \quad (1)$$

where, $S_{Lj,Gi}$ is the complex power contribution to load bus L_j by generator bus G_i.

B. Computation of electrical distances between generators and load buses

For computing the electrical distances between a generator bus and a particular load bus, the Z-Bus matrix of the network alone (excluding the effects of the loads) is first formed and by considering unit current injections into the particular generator bus and out of the particular load bus alone leaving all the other generator and load buses open, the Thevenin's impedance between the particular generator bus and the load bus is computed by elimination of all the other buses by adopting the Kron's network reduction procedure [10].

Using the above procedure, the Thevenin's impedance, Z_{ij} between the i^{th} Generator bus and the j^{th} load bus will be nothing but the off diagonal element of the reduced Z-Bus matrix between these two nodes.

C. Computation of moments

The contribution of complex power, to a particular load bus from each generator bus found using (1) is multiplied by the equivalent impedance (Z_{th}) between the same pair of buses to obtain the real and reactive power moments as follows.

$$\begin{aligned} Pmom_j^i &= \mathrm{real}(S_{CONT,ij} \times Z_{th,ij}) \\ Qmom_j^i &= \mathrm{imag}(S_{CONT,ij} \times Z_{th,ij}) \end{aligned} \quad (2)$$

Where,

$j = 1, 2, \ldots . G_N.$

$i = 1, 2, \ldots . L_N.$

G_N, L_N = Number of generator buses and number of vulnerable load buses respectively.

V. Generation of the Output Patterns

The next step is to compute the target output Viz. distance to voltage collapse in terms of the reactive power load increment for the onset of voltage collapse corresponding to each of the input patterns (operating points) of the system, using a continuation load flow type analytical method. The analytical method used in the present paper is based on Ref. [11]. This reference essentially evaluates the global response of a power system to variations in the nodal constraints. This approach has the capability to calculate how any specified system quantity is related to any two independent node parameters. Such a relationship can be visualized as a surface in three dimensions. The contour map of this surface with respect to the varying parameters provides a useful two dimensional representation of these relationships. The calculation procedure of computing these contours essentially involves two steps i) for finding the first point on a particular contour in the Q-V plane at a particular vulnerable load bus corresponding to a particular real power load at this load bus as a parameter and ii) for computing the sequence of points on this contour by a "predictor-corrector" iterative method. These contours are essentially the Q-V curves obtained at a particular load bus starting from a particular loading condition (operating point) and on gradual increment of the reactive loading at the bus. In this procedure on a particular run of the contour program, while incrementing the reactive power load, the points at which the different generators hit their limits, one by one, could be identified. Every time when a particular generator hits its reactive power limit it is converted to a P-Q bus and taking this as another base case a fresh contour program run is made to get a fresh Q-V nose curve. When the last generator bus hits its reactive power limit the corresponding contour obtained is taken as the final contour and the distance between the initial operating point corresponding to the particular ANN input pattern and the nose point on this final contour curve can be taken as the distance to voltage collapse for this operating point (load pattern).

VI. Design and Training OF ANN'S

The final step in the proposed voltage stability assessment is the design and training of a separate feed forward type of ANN for each of the vulnerable load buses, making use of the input-output patterns developed as explained in Sections IV and V. For each of these ANN's, number of inputs as many as thrice the number of generators in the system representing the moments between each generator and the vulnerable load bus, reactive power margin available at each generator bus and additionally the real and reactive power loads and voltage magnitude at the load bus, {thus the number of inputs to ANN totaling to (3* Number of Generators + 3)}, have been used at the input layer. A single neuron at the output layer representing the target output Viz. distance to voltage collapse for each pattern, obtained by successive running of the contour program (as described in Section V), has been used. By systematically trying various transfer functions in the different layers, the number of hidden layers and the number of neurons in the hidden layer, a suitable architecture of the ANN could be obtained for a particular system. For training the ANN, the Levenberg-Marquardt optimization procedure available in the MATLAB toolbox has been utilized [12].

VII. Test System and Results

The proposed method of voltage stability assessment in the present paper has been applied to the IEEE 30 bus test system. The data pertaining to this test system are given in Ref. [13]. This system comprises of 6 generators and 41 lines.

For this system, 500 different loading patterns were generated for each of the conditions explained in SEC II (i), (ii) and (iii). The total number of loading patterns generated is 1500. The quantum and location of reactive power load increments and real power load decrements (with respect to the peak real power loading conditions) on randomly selected multiple number of load buses have been done to generate all the loading patterns by running random number generation program repeatedly.

For each of these loading patterns, the modal analysis program has been run to identify the most vulnerable few load buses from the voltage stability point of view, using the bus participation factors of the first five minimum eigenvalues.

For the base case loading condition, the participation factors obtained for each of the minimum five eigenvalues are shown in Fig. 1. This figure shows how the bus participation factors of the load buses change as the system loadings and corresponding operating modes (eigenvalues) change. For the most critical 500 loading patterns and corresponding to each of the five minimum Eigenvalues, load buses 30, 29, 26, 19 and 14 are found to have the maximum participation factors. Therefore, these load buses are selected as the most vulnerable load buses for all realistic operating conditions. Five separate neural networks (one each for each vulnerable load bus) have been designed and corresponding input and output patterns were generated for these five most vulnerable load buses in the system.

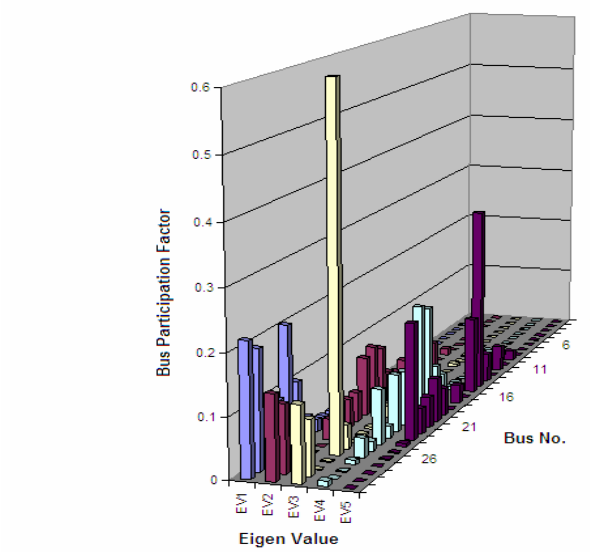

Fig 1 Participation Factors for first five minimum Eigenvalues for base case loading pattern.

A. *Generation of Patterns for ANN*

At each of the load buses thus selected, contribution of power-electrical distance i.e. real and reactive power moments between the particular load bus and all the six generators are calculated by running the power contribution computation program and electrical distance calculation program explained in Sec IV. The electrical distances (Z_{th}) calculated between any generator-load bus pair remains the same for all the loading patterns as the network parameters are only involved in this calculation and is independent of the bus loadings. However, the power contributions from different generators need to be calculated repeatedly as the loadings on the other buses also affect it. Reactive power margins (reserves) at all the six generator buses, voltage magnitude and real as well as reactive power loadings at that load bus have been calculated by running the load flow program repeatedly for all the 1500 loading patterns. Therefore, the total number of elements in the input vector for the test system are 3*6(number. of generators) + 3 =21.

For the i^{th} load bus, the input pattern vector is as follows

$$IP_i = [\,Qmar_{G1}, Qmar_{G2}, \ldots, Qmar_{GN}, Qmom^{Li}_{G1}, Qmom^{Li}_{G2}, \ldots, Qmom^{Li}_{GN}, Pmom^{Li}_{G1}, Pmom^{Li}_{G2}, \ldots, Pmom^{Li}_{GN}, Q_{Li}, P_{Li}, V_{Li}\,]^T$$

The distance to voltage collapse in terms of the reactive power-loading margin evaluated at a particular load bus has been used as the only target output for the ANN. The output of the contour program for various successive runs has been generated using the method explained in sec V. The Q-V curves drawn for bus No. 30 have been shown in Fig. 2. In this figure, contours of Q-V curves corresponding to the system real power peak loading conditions have been shown. It may be noted that the operating point of the system gets transferred from one QV curve to another QV curve as the Q limits on the generators are encountered one after the other. It may be observed that the Q limit of generator at bus 2 is reached at point 'A' and at this operating point in the further simulation this PV bus is converted to a PQ bus. The successive change-over points as the Q limit points at generators at buses 8,5,11 and 13 are shown as points B,C,D and E respectively. The point 'AA' would have been the point of voltage collapse on the QV curve, had the generator Q limits not been considered in the analysis. The point 'BB' shown in the figure is the point of voltage collapse when the Q limits on all the generators have been hit. The distance to voltage collapse, which is used as the target output of ANN for this particular pattern, is the Mvar margin between the current operating point 'O' and the voltage collapse point 'BB'. This Mvar margin turns out to be 0.3344 PU for the system studied. The Mvar margin would have been 0.3622 PU if the Q limits of the generators were not considered.

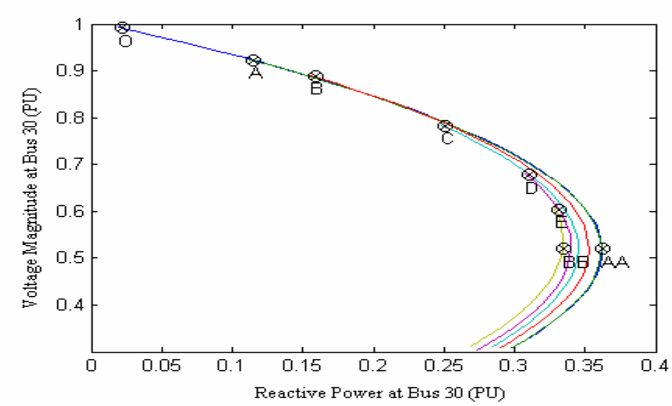

Fig 2 QV Curves and Point of collapse using proposed method for Base case loading

For each of the 1500 loading patterns the contour program is run once to find distance to the voltage collapse, which is used as the corresponding output pattern in the ANN training. The procedure is repeated for each of the most vulnerable buses in the system to generate the output patterns for each ANN corresponding to a vulnerable bus (bus no 30, 29, 26, 19, and 14).For each of these five ANN's, out of the total number of patterns generated, 80% of the patterns are used for the training of the ANN and the remaining 20 % are used for the testing purpose.

B. Training and testing of ANN

After trying many combinations of the number of hidden layers, Number of neurons in the hidden layer and the different transfer functions for the neurons in the hidden and output layers, the suitable architecture for the ANN has been arrived at. The suitable architecture for each of the five study load buses has been found to be the one having a single hidden layer with 10 neurons in it for the test system studied in this work. TANSIG transfer functions for the neurons at the hidden layer and PURELIN transfer function for the neuron at the output layer have been found to be appropriate. The training function for all the ANN is TRAINLM and the error function is MSE. The convergence characteristics and the minimum error achieved in the training of ANN both for the training patterns as well as for the fresh test patterns are presented in Table I.

The distances to voltage collapse (VCPI) obtained using the contour program and the trained ANN for the 300 test patterns have been compared in Fig. 3 to Fig. 7 for the different vulnerable load buses. Real power loadings are varied in the first 100 test patterns and reactive power loading are varied for the remaining 200 test patterns**.** It is observed that for the base case loading condition, the VCPI's found at bus no 14, 19, 26, 29 and 30 are 0.8047, 0.7995, 0.3214, 0.3629 and 0.334 PU respectively. The VCPI's found at bus 14, 19, 26, 29 and 30 are 0.5846, 0.5568, 0.2602, 0.2750 and 0.2722 PU for the 300th loading pattern. It is also observed that the change in VCPI at vulnerable load buses is highly nonlinear and its sensitivity to real and reactive power loading variations is different for different load buses. This characteristic of the VCPI at each load bus is also captured by the trained ANN, as the VCPI obtained from the trained ANN is closely matching with the VCPI obtained using the analytical method (contour program) for the test patterns which had not been used for training the ANN. It has been found that the maximum error in the VCPI, considering the errors in VCPI's for all the input-output patterns and for all the ANN's trained for the different vulnerable load buses, is 3.2% as shown in Table I. The error plot for the most critical load bus (Bus 30) for the 300 test patterns is shown in Fig. 8.

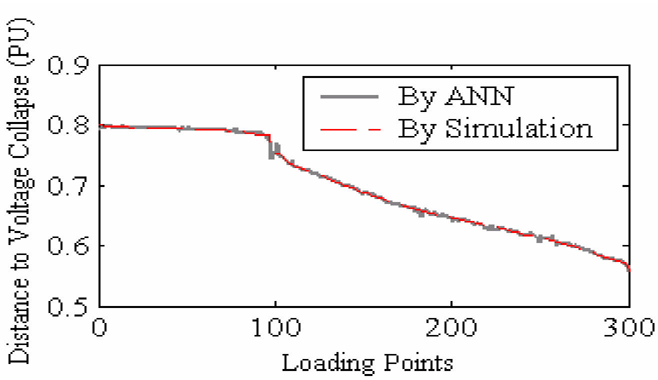

Fig 3 Simulated output and output from ANN at bus no 14.

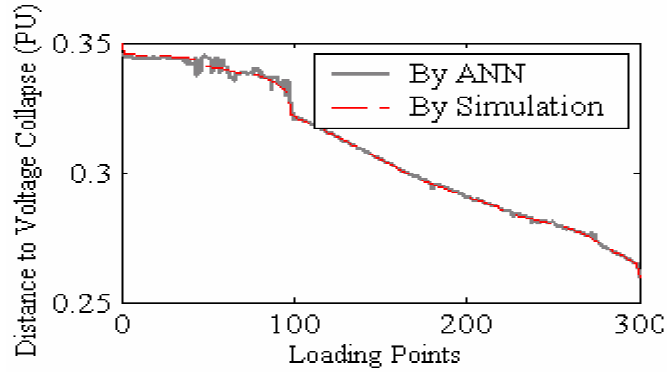

Fig 4 Simulated output and output from ANN at bus no 19.

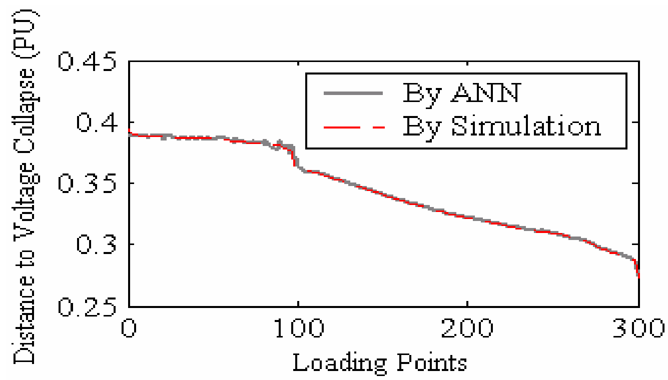

Fig 5 Simulated output and output from ANN at bus no 26.

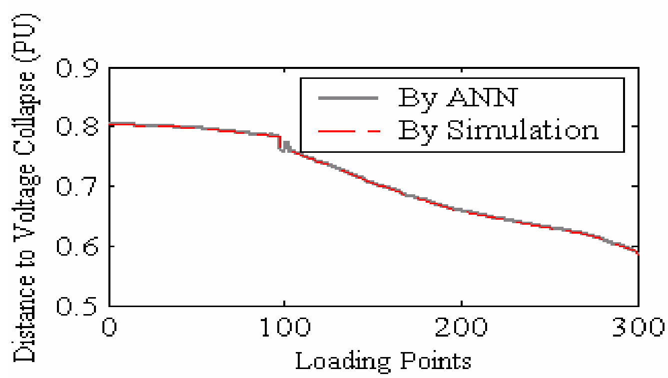

Fig 6 Simulated output and output from ANN at bus no 29.

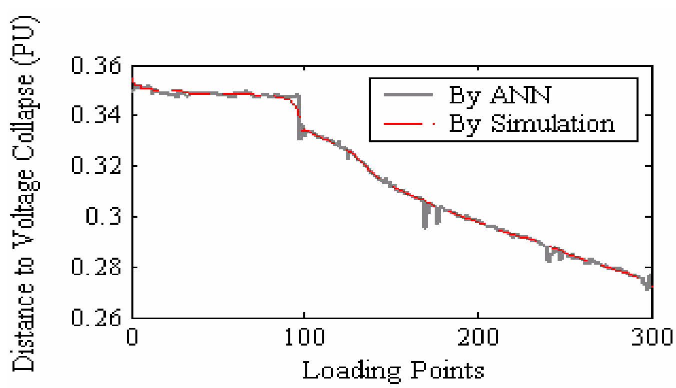

Fig 7 Simulated output and output from ANN at bus no 30.

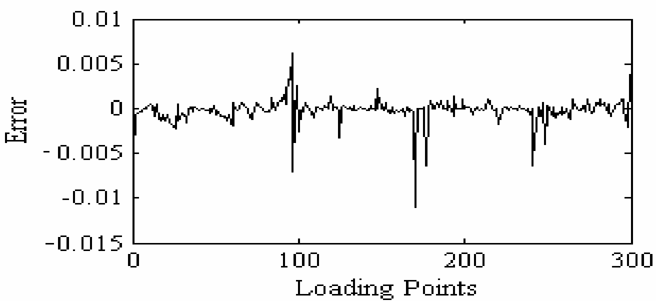

Fig 8 Error between Computed output and output from ANN at bus no 30

TABLE I
DETAILS OF TRAINING AND MAXIMUM ERROR IN OUTPUT

Bus no	No. of Epochs	MSE in the Training	Max Error in the testing pattern		
			DTC Simulated	DTC ANN	Max % error
14	100	1.78E-05	0.7601	0.7739	1.81
19	100	9.79E-05	0.7525	0.7683	2.06
26	200	0.0002	0.3222	0.3275	1.6
29	100	0.00011	0.3643	0.3719	2.1
30	250	0.00037	0.295	0.306	3.2

VIII. SUGGESTIONS FOR ONLINE APPLICATIONS

In addition to the method proposed in the paper being applied for planning purposes, it is expected that the trained ANN will be very useful for real-time monitoring and control of power systems. In the context of online applications, the following suggestions may be useful:

i) The real and reactive power loads, the voltage magnitude at the particular load bus and the reactive power margins available on all generators, used as the inputs to the ANN developed for that load bus could be directly obtained from the state estimation results corresponding to the current operating condition.

ii) The computation of the real and reactive power contributions by the different generators to the particular load bus involves only very few floating-point multiplications, as this computation involves only the modification of the [Zbus] of the network to include the effect of loads. The modified [Zbus] could be computed starting from the pre-calculated Zbus matrix of the complete system network (without any loads represented) and only modifying the matrix in real time to represent the loads at the current operating point, making use of the state estimation and the topological analysis results.

iii) The electrical distances between the different generator-load pairs could be pre-calculated and kept in the computer memory for the complete system configuration and could be modified in real time taking care of any topological changes and the current on-load transformer tap positions, following the procedure discussed in Section IV B.

iv) Simple multiplication of power contributions with the electrical distances for all the generator-vulnerable load bus pairs will be the Moments, which can be used as the additional inputs to the ANN

IX. CONCLUSION

An ANN based method has been proposed for on-line voltage stability assessment of power systems in this paper. The most vulnerable buses of the system from voltage stability point of view have been identified by Modal analysis. A separate feed forward type of ANN has been trained for each vulnerable load bus The ANN's are trained on wide range of loading patterns, covering all the heavy reactive power loading conditions. The proposed method has been applied to the IEEE 30 Bus Test System. Though the method has been proposed for a single area power system in the paper, it could be extended to an interconnected multi voltage control area power system by following the procedure for each voltage control area. Further, some suggestions for the application of the trained ANN's for real time monitoring of Voltage Stability of the system, utilizing the state estimation and system topology analysis results, have been made.

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XI. BIOGRAPHIES

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