01 Jan 1991

Security Assessment Using Neural Computing

Badrul H. Chowdhury
Missouri University of Science and Technology, bchow@mst.edu

B. M. Wilamowski

Recommended Citation

B. H. Chowdhury and B. M. Wilamowski, "Security Assessment Using Neural Computing," *Proceedings of the First International Forum on Applications of Neural Networks to Power Systems, 1991*, Institute of Electrical and Electronics Engineers (IEEE), Jan 1991.
The definitive version is available at https://doi.org/10.1109/ANN.1991.213497

SECURITY ASSESSMENT USING NEURAL COMPUTING

Badrul H. Chowdhury, Member IEEE

Bogdan M. Wilamowski, Senior member IEEE

Electrical Engineering Department
University of Wyoming
Laramie, WY 82071-3295

ABSTRACT

The advantage of fast computation capability of an Artificial Neural Network (ANN) is used to introduce an iterative scheme for security assessment of power systems. Two related approaches are shown which demonstratedly work satisfactorily. The idea of feedback in a single-layer feedforward neural network is experimented yielding higher accuracy. The ANN is trained by using a set of data obtained from off-line analysis of the power network. After training, an approximate solution for a given condition may be found almost immediately. The approximate solution obtained is judged adequate for assessing the security of the power system. A case study is also presented for demonstrating the applicability of the approach.

Keywords: Artificial neural network, training set, contingency, projection algorithm.

1. INTRODUCTION

Security assessment of power systems is a difficult problem which, with traditional approaches requires enormous computational effort. Contributing to the complexity of the task are: (i) the constantly changing system demands and generations, and (ii) an often inexhaustible list of contingencies that need to be evaluated in real time. Each contingency requires solving a large set of non-linear equations in order to obtain information on potential line overloads or bus voltage magnitude deviations from their limits. These non-linear equations are normally solved by using any of the widely acclaimed power flow solution techniques viz., the Gauss-Seidel method, the Newton-Raphson method or in some cases, the fast decoupled method. The Gauss-Seidel method has a relatively simple algorithm but it requires many iterations and for some large power systems, the method may not converge to the solution. The Newton-Raphson method also requires an iterative solution of a large set of non-linear equations but algorithm converges faster. However, the method is memory-intensive even with application of sparse matrix techniques. The fast-decoupled method is the most efficient, however in some cases, only an approximate solution may be found.

This paper presents results of experimentation with an Artificial Neural Network (ANN) for security assessment of a power system. The paper presents arguments toward the concept that the conventional tedious approach to obtaining solutions of a power network by using numerical methods may be avoided by using neural computing. The ANN is trained by using a set of data obtained from off-line analysis of the power network. After training, an approximate solution for any given condition, may be found almost immediately. The approximate solution is accurate enough for adequately assessing the security of the power system. A case study is presented later in the paper.

The concept of applying ANN's to static and dynamic security assessment is a relatively new concept. Several authors in the past few years have investigated the suitability of applying this particular branch of artificial intelligence in mitigating the problems of traditional approaches to security evaluation in power systems [1-5]. These studies have brought into perspective several key issues relating to the new art. In general, research interest in application of neural networks in power systems operations and planning is on the rise as evident from a recently concluded workshop [6].

2. POSSIBLE APPROACHES FOR NEURAL COMPUTING

In static security assessment, one needs to investigate for a set of real and reactive powers on buses, the condition of line flows exceeding the maximum ratings and bus voltage deviations from their lower and upper limits. In alternate terms, for a given vector of bus powers, a vector of line flows and bus voltage magnitudes has to be determined and evaluated. The most straightforward explanation of such an approach is shown in Fig. 1.

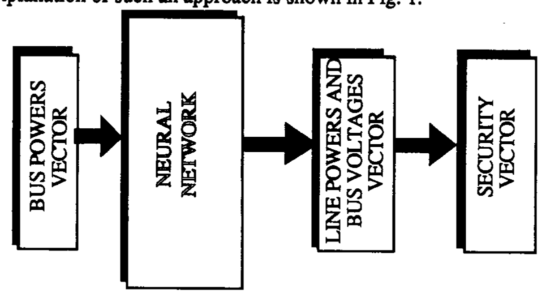

Figure 1. A possible approach for security assessment

The set of power flow equations is modeled by one layer of the feedforward neural network as shown in Fig. 2.

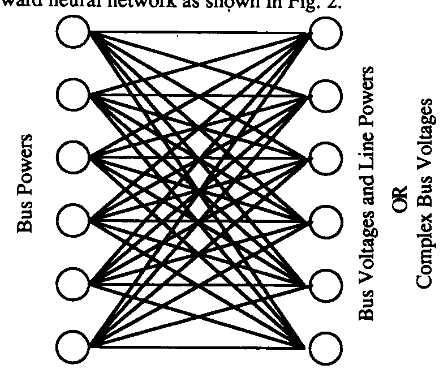

Fig.2 One layer neural network

If powers at the buses are known, then by using the trained neural network, approximate values of the bus voltages and line powers can be found. Then, having the vector of line flows and the vector of bus voltages, the security vector can be found by setting appropriate thresholds for maximum line ratings, and lower and upper bounds for the voltage magnitudes. The term "security vector" will be used in this paper in the context of branches overloaded and buses having voltages outside the limits.

Another possible approach for security assessment is to use the method shown in Fig. 3, where the ANN is used only to determine the vector of bus voltages. Thereafter the vector of average line currents $\hat{I}_{ij}$ and the vector of complex line flows $\hat{S}_{ij}$ may be explicitly calculated using the following equations:

$$\hat{I}_{ij} = \frac{\hat{V}_i - \hat{V}_j}{\hat{Z}_{ij}} + H_{ij}\frac{\hat{V}_i - \hat{V}_j}{2} \qquad (1)$$

and

$$\hat{S}_{ij} = (\hat{V}_i - \hat{V}_j)\hat{I}_{ij} \qquad (2)$$

where:

$\hat{V}_i$ - complex voltage at bus i.
$\hat{V}_j$ - complex voltage at bus j.
$\hat{Z}_{ij}$ - series line impedance between buses i and j.
$\hat{H}_{ij}$ - half-line susceptance between buses i and j.
$\hat{I}_{ij}$ - complex line current from bus i to bus j.
$\hat{S}_{ij}$ - complex line flow from bus i to bus j.

Since the output vector shown in Fig. 1 contains both branch data and bus data, the ANN used in the first approach will have a larger number of neurons to train compared to the ANN used in the second approach.

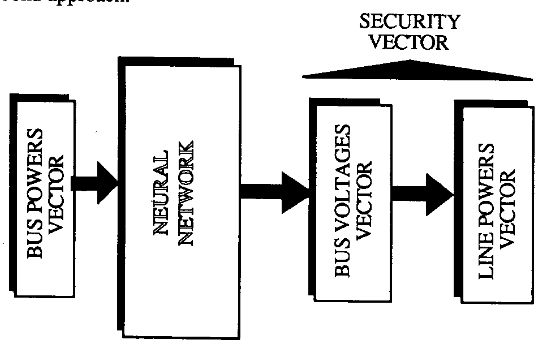

Figure 3. An alternate approach for security assessment

2.1 Contingency Analysis for Generator Failure

Predicting the effect of the failure of a generator is a relatively easy task with the ANN. This is simulated by a simple change in the input vector (the generated real and reactive powers on that bus is forced to zero). As a result the voltage distributions under such a contingency may be computed by the ANN. As a next step line currents can be computed from Eqs. 1 and 2. Having values of line currents, system security can be computed as a simple sum of the cases where the parameter ranges are violated.

For proper operation, it is essential that bus voltages obtained from the ANN are high in accuracy. The training method applied, plays a key role in attaining the desired accuracy. For a given power system, the ANN can be trained using, for example the back propagation algorithm which is very slow and may require hundreds or even thousands of iterations depending on the size of the system. However, for the test system used for demonstration in the paper, it was found that the projection algorithm based on the least squares approximation technique was more efficient. Since an ANN without hidden layers is used, the projection algorithm proved to be very stable and accurate.

In order to further increase accuracy of the solutions, a feedback is applied to the feedforward ANN as shown in Fig. 4. A vector of bus power for feedback, $\bar{S}_{bf}$ is computed simply as a sum of line flows S_{km} at each bus k. At the initial state, elements of the vector of line power are zeros and hence the feedback vector is zero. Therefore, in the first step, the input vector of bus powers S_b is applied to the neural network and an approximate initial vector of line powers $S_{km,o}$ is obtained. In the second step, the difference between the input vector of bus powers S_b and the feedback vector $\bar{S}_{bf}$ is input to the ANN. Hence, the neural network operates on the difference (error) and the vector of line powers at the output is corrected. Usually a few iterations are enough in order to obtain convergence.

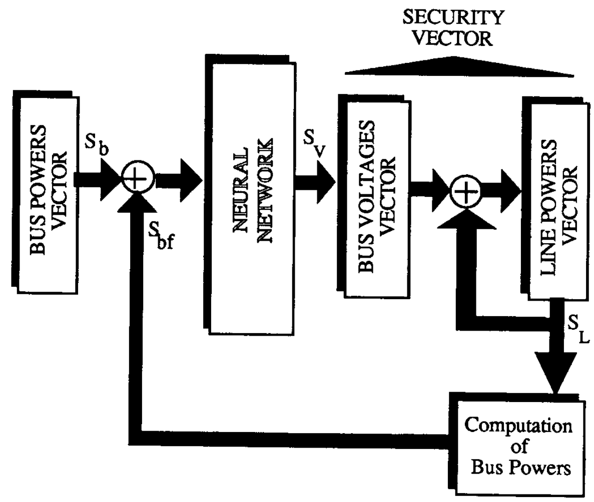

Fig. 4. The feedforward ANN with feedback

2.2 Contingency Analysis for Line Failure

A more difficult task is to provide analysis in the case of line failures. In general when a line fails, the power network topology changes and results obtained from the previously trained ANN can be misleading. For each possible line failure, the ANN should be trained in order to obtain correct values of bus voltages and line flows for any given power distribution. This is a rather time-consuming approach and therefore not considered to be practical.

In order to simulate a line failure, the following iterative algorithm is used. Instead of changing the system topology by taking the line out of the system, two additional complex power sources are introduced in relation to the failed line as shown in Fig. 5.

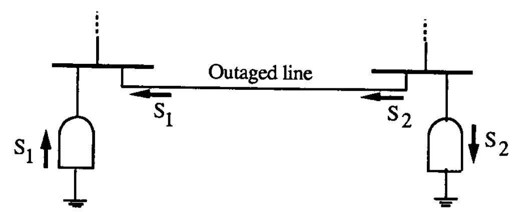

Figure 5. Power compensation method used for simulating line outages

The two added power sources shown in the figure have the same values as the line flows measured at each bus, but have opposite direction relative to the outaged line flow. This is done in order to initially obtain zero net power flow between the buses connected by the failed line. However, these initial net complex power compensation may not result in zero power flow between the buses because of changes in conditions in the rest of the power network as a result of adding the extra sources. This may cause under- or over-compensation. To circumvent this problem, a modification to the computational scheme shown in Fig. 4 was implemented in the feedback loop block of "Computation of bus powers." If a certain line would fail, then the power flow existing in the failed line prior to the outage is added to the complex powers of the associated buses as shown in Fig. 5. Using this iterative scheme and with the minor correction to the computational algorithm, very accurate results can be obtained without the need for changing the topology of the network. With the proposed approach, we are merely adding extra power sources to the system; hence it is not necessary to re-train the ANN for each line contingency.

Table 1. The Training Set for the ANN.

-20.000	-30.000	-20.000	-20.000	-20.000	-20.000	15.000	20.000	-0.877	1.028	-1.280	1.036	-1.254	1.037	-0.645	-0.651
-30.000	-30.000	-30.000	-20.000	-30.000	-20.000	20.000	30.000	-1.578	1.026	-2.087	1.033	-2.075	1.035	-1.144	-1.102
-40.000	-30.000	-35.000	-20.000	-35.000	-20.000	25.000	40.000	-1.946	1.023	-2.287	1.031	-2.157	1.034	-1.195	-0.898
-40.000	-35.000	-35.000	-25.000	-35.000	-25.000	25.000	40.000	-1.900	1.020	-2.233	1.027	-2.140	1.030	-1.229	-0.926
-45.000	-35.000	-40.000	-25.000	-40.000	-25.000	35.000	40.000	-2.147	1.018	-2.617	1.025	-2.568	1.029	-1.295	-1.275
-45.000	-40.000	-40.000	-30.000	-40.000	-30.000	35.000	40.000	-2.098	1.015	-2.563	1.021	-2.549	1.026	-1.327	-1.302
-48.000	-40.000	-50.000	-30.000	-45.000	-30.000	45.000	42.000	-2.324	1.014	-3.131	1.018	-3.026	1.024	-1.421	-1.664
-48.000	-45.000	-50.000	-32.000	-45.000	-38.000	45.000	42.000	-2.276	1.010	-3.107	1.015	-2.986	1.019	-1.451	-1.684
-55.000	-45.000	-75.000	-32.000	-50.000	-38.000	65.000	50.000	-2.639	1.007	-4.181	1.008	-3.479	1.017	-1.448	-1.960
-55.000	-50.000	-75.000	-50.000	-50.000	-45.000	65.000	50.000	-2.600	1.002	-4.009	0.994	-3.473	1.011	-1.520	-2.040
-70.000	-50.000	-70.000	-50.000	-70.000	-45.000	65.000	55.000	-3.879	0.999	-4.966	0.995	-5.341	1.007	-2.705	-3.432
-70.000	-70.000	-70.000	-70.000	-70.000	-70.000	65.000	55.000	-3.732	0.984	-4.812	0.975	-5.329	0.989	-2.911	-3.637
-80.000	-70.000	-75.000	-70.000	-80.000	-70.000	70.000	60.000	-4.504	0.982	-5.614	0.973	-6.361	0.987	-3.523	-4.383
-85.000	-70.000	-95.000	-70.000	-90.000	-70.000	75.000	80.000	-4.955	0.979	-6.539	0.966	-6.864	0.984	-3.799	-4.305
-85.000	-75.000	-95.000	-80.000	-90.000	-80.000	75.000	80.000	-4.934	0.975	-6.473	0.957	-6.873	0.977	-3.892	-4.400
-90.000	-75.000	-105.000	-80.000	-100.000	-80.000	90.000	100.000	-4.656	0.972	-6.249	0.953	-6.282	0.974	-3.136	-3.212
-90.000	-80.000	-105.000	-90.000	-100.000	-90.000	90.000	100.000	-4.648	0.968	-6.191	0.943	-6.304	0.966	-3.236	-3.320
-95.000	-80.000	-125.000	-90.000	-130.000	-90.000	100.000	120.000	-5.707	0.966	-8.149	0.935	-8.717	0.959	-4.367	-4.745
-125.000	-100.000	-145.000	-120.000	-150.000	-120.000	150.000	170.000	-5.293	0.935	-7.089	0.892	-6.768	0.928	-2.444	-1.587
-145.000	-100.000	-165.000	-120.000	-170.000	-120.000	190.000	160.000	-6.963	0.928	-9.674	0.882	-9.846	0.920	-3.545	-4.494
-165.000	-120.000	-165.000	-130.000	-150.000	-130.000	180.000	190.000	-7.727	0.904	-8.000	0.869	-6.700	0.917	-2.578	-1.205
-185.000	-120.000	-185.000	-130.000	-180.000	-130.000	210.000	210.000	-8.170	0.895	-9.998	0.856	-9.001	0.907	-3.345	-2.249

3. CASE STUDY

In order to test the algorithm for its effectiveness in predicting system security we selected a simple six-bus test system [7] as shown in Fig. 6.

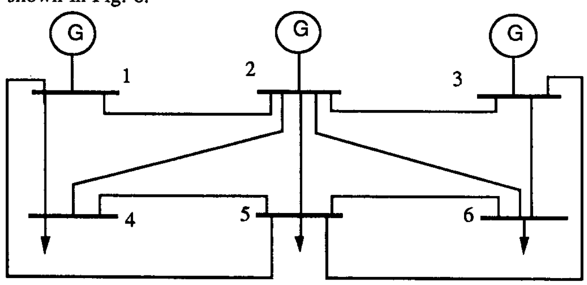

Figure 6. Experimental test system used in the simulation

The training set is shown in Table 1. It consists of 22 vectors of input data and the same number of output vectors. Each input vector has the following elements:

$$[P_4, Q_4, P_5, Q_5, P_6, Q_6, P_2, P_3,]^T$$

and each output vector has:

$$[\delta_4, |V_4|, \delta_5, |V_5|, \delta_6, |V_6|, \delta_2, \delta_3,]^T$$

The real and reactive powers have units of MW and MVars respectively and the voltage magnitudes and angles are given in per unit and degrees, respectively.

After training is completed, the ANN is tested for validation. A set of new input training vectors are applied to the neural network. Table 2 shows 5 such test input vectors and Table 3 shows comparisons of corresponding bus voltages and line flows as computed by the ANN against values obtained by off-line computer analysis using a rigorous mathematical power flow model. Results shown in Table 3 are for the case when no feedback is used in the ANN. Also noteworthy is the fact that not all line flows are shown on the table for the reason of brevity. Table 4 is similar to Table 3 except that a feedback loop was incorporated into the ANN. It may be observed that the case with feedback yields more accurate results.

Table 2. Test Input Vectors for the Trained Neural Network

Test#	P_4	Q_4	P_5	Q_5	P_6	Q_6	P_2	P_3
1	- 43	-32	- 38	- 18	- 32	- 28	34	35
2	- 50	-37	- 56	- 40	- 32	- 30	53	49
3	- 82	-66	- 71	- 62	- 65	- 65	60	75
4	- 92	-72	-110	- 85	- 93	- 82	98	89
5	-135	-90	-156	-132	-165	-124	145	180

Table 3. Validation of Bus Voltages and Line Flows (No Feedback)

	BUS VOLTAGES	ANN	Actual	LINE FLOWS	ANN	Actual
T	$\lvert V_4\rvert$ =	1.02247	1.02108	1-2:	7.99	9.00
E	δ_4 =	-1.7821	-1.9240	1-4:	21.27	22.69
S	$\lvert V_5\rvert$ =	1.03185	1.03077	2-4:	25.56	26.78
T	δ_5 =	-2.1894	-2.3606	2-6:	11.35	11.64
#	$\lvert V_6\rvert$ =	1.02982	1.02965	3-6:	27.20	28.34
1	δ_6 =	-1.8620	-2.0197	5-6:	2.03	2.03
T	$\lvert V_4\rvert$ =	1.01162	1.01282	1-2:	3.25	3.36
E	δ_4 =	-1.6579	-1.6513	1-4:	24.25	23.76
S	$\lvert V_5\rvert$ =	1.00869	1.01022	2-4:	38.34	37.26
T	δ_5 =	-2.1357	-2.1333	2-6:	12.67	12.82
#	$\lvert V_6\rvert$ =	1.02495	1.02501	3-6:	33.78	34.23
2	δ_6 =	-1.1799	-1.2281	5-6:	7.53	7.01
T	$\lvert V_4\rvert$ =	0.98270	0.98405	1-2:	21.17	20.58
E	δ_4 =	-3.8673	-3.7943	1-4:	47.26	46.39
S	$\lvert V_5\rvert$ =	0.97922	0.98128	2-4:	60.80	59.70
T	δ_5 =	-4.2537	-4.1726	2-6:	28.07	27.64
#	$\lvert V_6\rvert$ =	0.99372	0.99489	3-6:	67.22	66.48
3	δ_6 =	-4.0451	-3.9837	5-6:	4.63	4.34
T	$\lvert V_4\rvert$ =	0.97397	0.97294	1-2:	26.10	27.19
E	δ_4 =	-4.6641	-4.8183	1-4:	54.88	56.16
S	$\lvert V_5\rvert$ =	0.94950	0.94782	2-4:	69.11	70.08
T	δ_5 =	-6.3593	-6.5527	2-6:	43.21	43.56
#	$\lvert V_6\rvert$ =	0.97364	0.97323	3-6:	88.24	89.26
4	δ_6 =	-6.2389	-6.4079	5-6:	7.30	7.69
T	$\lvert V_4\rvert$ =	0.94127	0.93739	1-2:	31.43	35.13
E	δ_4 =	-6.4609	-6.9309	1-4:	75.17	79.05
S	$\lvert V_5\rvert$ =	0.88395	0.87684	2-4:	101.60	104.72
T	δ_5 =	-8.2686	-8.8373	2-6:	68.09	70.04
#	$\lvert V_6\rvert$ =	0.9240	0.91876	3-6:	152.58	157.31
5	δ_6 =	-8.4162	-9.0166	5-6:	10.90	11.82

Table 4. Validation of Bus Voltages and Line Flows (With Feedback)

		BUS VOLTAGES ANN	Actual	LINE FLOWS	ANN	Actual
T	$\|V_4\|$ =	1.02117	1.02108	1-2:	9.10	9.00
E	δ_4 =	-1.9331	-1.9240	1-4:	22.72	22.69
S	$\|V_5\|$ =	1.03076	1.03077	2-4:	26.69	26.78
T	δ_5 =	-2.3694	-2.3606	2-6:	11.64	11.64
#	$\|V_6\|$ =	1.02968	1.02965	3-6:	28.29	28.34
1	δ_6 =	-2.0334	-2.0197	5-6:	2.00	2.03
T	$\|V_4\|$ =	1.01287	1.01282	1-2:	3.41	3.36
E	δ_4 =	-1.6607	-1.6513	1-4:	23.80	23.76
S	$\|V_5\|$ =	1.01018	1.01022	2-4:	37.22	37.26
T	δ_5 =	-2.1398	-2.1333	2-6:	12.82	12.82
#	$\|V_6\|$ =	1.02504	1.02501	3-6:	34.21	34.23
2	δ_6 =	-1.2384	-1.2281	5-6:	7.01	7.01
T	$\|V_4\|$ =	0.98404	0.98405	1-2:	20.67	20.58
E	δ_4 =	-3.7991	-3.7943	1-4:	46.43	46.39
S	$\|V_5\|$ =	0.98131	0.98128	2-4:	59.67	59.70
T	δ_5 =	-4.1821	-4.1726	2-6:	27.63	27.64
#	$\|V_6\|$ =	0.99490	0.99489	3-6:	66.46	66.48
3	δ_6 =	-3.9947	-3.9837	5-6:	4.33	4.34
T	$\|V_4\|$ =	0.97293	0.97294	1-2:	27.25	27.19
E	δ_4 =	-4.8207	-4.8183	1-4:	56.18	56.16
S	$\|V_5\|$ =	0.94784	0.94782	2-4:	70.05	70.08
T	δ_5 =	-6.5598	-6.5527	2-6:	43.55	43.56
#	$\|V_6\|$ =	0.97324	0.97323	3-6:	89.24	89.26
4	δ_6 =	-6.4154	-6.4079	5-6:	7.69	7.69
T	$\|V_4\|$ =	0.93747	0.93739	1-2:	35.08	35.13
E	δ_4 =	-6.9307	-6.9309	1-4:	79.02	79.05
S	$\|V_5\|$ =	0.87694	0.87684	2-4:	104.69	104.72
T	δ_5 =	-8.8294	-8.8373	2-6:	70.02	70.04
#	$\|V_6\|$ =	0.91881	0.91876	3-6:	159.24	157.31
5	δ_6 =	-9.0101	-9.0166	5-6:	11.81	11.82

The performance of the ANN was then tested for predicting contingency conditions which translates into security assessment. Table 5 shows the input vectors used and the contingencies tested in this phase of the study. All powers are shown in MW and MVars. Table 6 shows comparisons of the ANN outputs against those obtained by using a power flow computer model. Some inaccuracies may be noted in Test cases 1, 2 and 4 of Table 6. The reason was the fact that during numerical computation of power flows, it was found that the generator at bus 2 for case 1, generators at buses 2 and 3 for case 2, and generator at bus 2 for case 4 respectively had exceeded their var limits and had lost voltage control. No such control action was incorporated in the design of the ANN and hence the inaccuracies.

Table 5. Inputs Used for the Test Contingencies

Test Case	P_4	Q_4	P_5	Q_5	P_6	Q_6	P_2	P_3
1. Gen out at bus 2	-135	-90	-156	-132	-165	-124	0	180
2. Line out: 1-4	-135	-90	-156	-132	-165	-124	145	180
3. Line out: 2-3	-135	-90	-156	-132	-165	-124	145	180
4. Line out: 3-5	-135	-90	-156	-132	-165	-124	145	180
5. Line out: 5-6	-135	-90	-156	-132	-165	-124	145	180

Table 6. Comparisons of Test Contingencies

		BUS VOLTAGES ANN	Actual	LINE FLOWS	ANN	Actual
T	$\|V_4\|$ =	0.93995	0.92392	1-2:	114.72	110.84
E	δ_4 =	-13.091	-13.0169	1-4:	120.39	121.91
S	$\|V_5\|$ =	0.87590	0.86450	2-4:	93.43	85.94
T	δ_5 =	-15.2167	-15.3047	2-6:	65.17	60.42
#	$\|V_6\|$ =	0.91932	0.90974	3-6:	157.25	163.54
1	δ_6 =	-17.2701	-17.4265	5-6:	15.22	15.57
T	$\|V_4\|$ =	0.8645	0.79971	1-2:	93.43	91.94
E	δ_4 =	-16.2398	-17.1182	1-5:	92.67	99.46
S	$\|V_5\|$ =	0.86336	0.82533	2-4:	170.96	172.26
T	δ_5 =	-14.4657	-15.1891	2-6:	69.16	62.16
#	$\|V_6\|$ =	0.91643	0.88341	3-6:	158.62	170.20
2	δ_6 =	-15.4939	-16.3792	5-6:	15.45	16.26
T	$\|V_4\|$ =	0.93753	0.93745	1-2:	35.79	35.84
E	δ_4 =	-6.9569	-6.9577	1-4:	79.16	79.19
S	$\|V_5\|$ =	0.87689	0.87678	2-4:	104.29	104.32
T	δ_5 =	-8.6551	-8.6644	2-6:	68.17	68.20
#	$\|V_6\|$ =	0.91910	0.87678	3-6:	159.38	159.44
3	δ_6 =	-8.6806	-8.6888	5-6:	11.88	11.89
T	$\|V_4\|$ =	0.92633	0.92092	1-2:	29.68	29.73
E	δ_4 =	-6.7997	-6.8695	1-4:	81.32	83.25
S	$\|V_5\|$ =	0.80765	0.79785	2-4:	116.10	115.76
T	δ_5 =	-10.4793	-10.7502	2-6:	69.35	68.78
#	$\|V_6\|$ =	0.90595	0.90151	3-6:	183.14	186.73
4	δ_6 =	-6.9633	-7.0479	5-6:	30.00	31.31
T	$\|V_4\|$ =	0.93807	0.93485	1-2:	35.97	35.44
E	δ_4 =	-7.0244	-6.9766	1-4:	79.43	80.00
S	$\|V_5\|$ =	0.88057	0.85992	2-4:	104.18	106.66
T	δ_5 =	-9.1324	-8.8581	2-6:	68.11	66.77
#	$\|V_6\|$ =	0.92623	0.92738	3-6:	152.96	150.86
5	δ_6 =	-9.2336	-8.9642	4-5:	13.41	15.96

4. CONCLUSIONS

Computation time for security assessment using a trained neural network approach is significantly shorter than that required by numerical analysis under identical contingencies. A single layer ANN was experimented for this purpose and the projection algorithm was used for training. Results obtained were generally comparable to actual output from numerical computations and no need was felt for experimentation with a multi-layer neural network. For a given power system, the ANN has to be trained only once and subsequently will operate for any load condition in the system. This includes normal power system operating condition operation with no outages as well as for operating conditions under contingencies of generator and line outages. A new algorithm was developed in order to incorporate line outage condition into the ANN. Very accurate results could be obtained without the need for changing the topology of the network under contingencies. With this approach, it was not necessary to re-train the ANN for each line contingency. Test results from a case study on a small power system are shown. A degree of accuracy can be seen from comparisons with actual results.

Although the test case shown in the paper deals with a small and simple power network, the approach described can be easily extended to much larger and complex systems. We believe that with larger networks, a somewhat larger input training vector having information on tap-changing transformers, phase-shifting transformers, reactive compensators, capacitors and synchronous condensers will be required. We are confident that the solution time for the ANN execution will not slow down considerably with a larger network because about 90 per cent of the weights found for the neurons will be insignificant.

5. REFERENCES

[1] D. J. Sobajic and Y. H. Tao, "Artificial Neural Net Based Dynamic Security Assessment for Electric Power Systems," *IEEE Trans. PWRS,* Vol. 4, 220-228, 1989.

[2] R. Fischl, M. Kam, J. C. Chow, S. Ricciardi, "Screening Power System Contingencies Using a Back Propagation Trained Multiperception," *Proc. 1989 Int. Sym. on Circuits and Systems.*

[3] M. E. Agounne, L. E. Atlas, D. A Cohn, M. J. Damborg, M. A. El-Sharkawi, R. J. Marks II, "Artificial Neural Networks for Power System Static Security Assessment," *Proc. 1989 Int. Sym. on Circuits and Systems.*

[4] M. Agounne, M. A. El-Sharkawi, D. C. Parks, M. J. Damborg, R. J. Marks II, "Preliminary Results on Using Artificial Neural Networks for Security Assessment," *Proc. 1989 PICA Conference*, 252-258.

[5] M. A. El-Sharkawi, R. J. Marks II, M. E. Agounne, D. C. Parks, M. J. Damborg, L. E. Atlas, "Dynamic Security Assessment of Power Systems Using Back Error Propagation Artificial Neural Networks," *2nd Sym. on Expert Systems Application to Power Systems*, Seattle, WA, July, 1989.

[6] Clemson University, *Workshop on Application of Artificial Neural Network Methodoogy in Power System Engineering*, Clemson, SC, April, 1990.

[7] A. J. Wood, B. F. Wollenberg, *Power Generation, Operation and Control,* John Wiley & Sons, Inc., 1984.