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Contingency Ranking for Power System Using Multilayer Feed Forward Neural Network

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ABSTRACT

This paper presents a supervising learning approach using Multilayer Feed Forward Neural Network(MFFN) and to deal with fast and accurate static security assessment (SSA) and contingency analysis of a large electric power systems. The degree of severity of contingencies is measured by two scalar performance indices (PIs): Active power performance index PI_P and voltage performance index, PI_V. For each (N-1) contingency, the Performance Index (PI) is computed using the Newton Raphson load flow (NRLF) method.N-1 line outage contingencies are used as input features to train the neural network models, to predict the performance indices for unseen network conditions and rank them in descending order based on performance indices for security assessment. The proposed method has been applied on an IEEE 57-bus test system at different operating conditions comparing to single line outage and the results demonstrate the suitability of the methodology for on-line power system security assessment at Energy Management Center. The performance of the proposed ANN model is compared with Newton Raphson (NR) method and the results shows that the proposed model is effective and reliable in terms of static security assessment of power systems.

Keywords: PerformanceIndex, Static Security Assessment, Contingency Analysis, Supervised Learning, Multilayer Feed Forward Neural Network.

I. INTRODUCTION

Security assessment of a power systemplays an important role for on-line applicationsat Energy Management Centerwhich employs to examine the steady state performance of a power system after contingency. Now days, electric power system move towards a new environment that is deregulation which has forced modern electric utilities to operate their systems under highly stressed conditions closer to their security limits. Therefore, the system operators needs to develop quick and more precise ranking methods for analyzing the power system security violations and severity level of contingencies to keep the power system in safe operating limits. In the area of the power system static security assessment, the contingency analysis plays a vital role, the importance of which is discussed in [1].

The contingency analysis gives the security state of the power system under a contingency. The several load flow methods to perform the contingency analysis such as the Gauss-Seidal (GS), the Newton-Raphson (NR) and the fast decoupled (FD) methods [2] were used. These methods are used to obtain the load flow solutions under the contingency conditions, which helps in computation of the system severity. Using AC load flow solution in to determine the outage cases with respect to the reactive power and voltage magnitudes are discussed in [3]. In [4, 5], in order to calculate the distribution factors the accurate methods are discussed which are based on the decoupled and the Newton-Raphson load flow considering network sensitivities. Computation

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of the post-outage reactive power flows and the voltage magnitudes following a transmission line or a generator outage are done with obtained distribution factors.

The AC load flow method is not feasible to perform online, because it should be solved for each contingency case in order to evaluate the limit violations. To overcome this computational barrier various approximate methods have been developed. There available two techniques known as the explicit and the implicit techniques. The explicit methods are discussed in [6, 7].These are the ranking methods, where the contingencies are ranked based on the order of severity using a scalar performance index (PI), which measures the system stress. Higher severity is ranked first and going down the list with the least severity. Whereas, implicit methods are discussed in [8, 9]. This method applies network solutions in order to recognize the system violations and rank the severity for the various outages.

The ideal approach for the static security assessment of a power network is by contingency ranking. The concept of the contingency ranking was introduced by Ejebe and Wollenberg, in which the contingencies are arranged in descending order by considering the performance index [10]. In [6,7,10,11] automatic contingency selection focused mostly on implementing algorithms in order to rank the contingencies based on the impact on active power flows and then extending the algorithms to rank the contingencies based on its impact on bus voltages. A direct ranking method, in which the performance index for a contingency case do not require post contingency voltages at each bus for ranking, have proposed by Yilang chen et al. in [12] . In [13] the authors have applied the decoupled load flow and the compensation method in order to obtain post outage voltages, and the ranking is given based on performance index. Conventionally, the contingency ranking approach is performed based on the performance indices (PI) obtained after solving the load flow solutions In this approach, the contingencies are ranked based on the severity obtained from network variables and are directly assessed. These methods are highly complex, time consuming and the system operating conditions have variation with time. So the conventional methods infeasible for real time implementation. Thus, there is a need to develop efficient online tool (which monitor the system security under variable system conditions) for the power system security assessment to ensure safe operation of the power system [14].

Thus in the recent years, the literature revealed the application of the artificial neural networks (ANN) to power system static security assessment. The computation speed and generalization capability of ANN makes it feasible for the modern power systems for the security monitoring [15]. In [16, 17], the authors have investigated the application of pattern recognition technique with forward only counter propagation network for the active power contingency ranking. The efficient performance of the ANN is observed because of the suitable selection of training features which covers the entire operating states of the powersystem.

The collective use of supervised and unsupervised learning in power system analysis has been used to overcome the slow rate of convergence and local minima problem faced in multilayer perceptron neural network using back propagation training [18].

II. POWER SYSTEM SECURITY ASSESSMENT BY CONTINGENCY RANKING APPROACH USING NEWTON RAPHSON LOAD FLOW METHOD

The Contingency analysis with the use of AC power flow gives the advantage that it provides power flows in terms of MW, MVAR and bus voltage magnitudes. Using the AC power flow, overloads and accurate voltage limit violations. In the present work, for the contingency ranking outages of each line has been considered.

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Performance indices (PI) are considered for ranking the severity of a particular contingency. Conventional power flow methods are used in calculating the indices in an offline mode. After obtaining the values obtained using conventional method are sorted out in descending manner and the highest value of PI is ranked first.

There are two types of performance index which are mainly used to obtain contingency severity.

Active Power performance index (PI_p):This is the index which helps in determining the extent of line overloading.

$$PI_p = \sum_{l=1}^{N_L} \left(\frac{W}{2n}\right)\left(\frac{P_l}{P_l^{max}}\right)^{2n} \qquad (1)$$

Where,

P_l is the MW power flow of line *l*

P_l^{max} is the MW capacity of line *l*

N_L is the number of lines of the system

W is the real non-negative weighting factor, and value is (= 1)

n is exponent of penalty function and value is (=1)

$$P_l^{max} = \frac{(V_i * V_j)}{X} \quad (2)$$

Where,

V_i is the voltage at bus i^{th} obtained from the NR solution

V_j is the voltage at bus j^{th} obtained from the NR solution

X is the reactance of the line connecting i^{th} bus and j^{th} bus.

Voltage performance index (PI_V):This is the index which helps in determining the extent of bus voltage limit violation.

$$PI_v = \sum_{i=1}^{N_B} \left(\frac{W}{2n}\right)\left(\frac{(|V_i| - |V_i^{sp}|)}{\Delta V_i^{lim}}\right) \qquad (3)$$

Where,

$|V_i|$ is the voltage magnitude at i^{th} bus.

$|V_i^{sp}|$ is the specified (rated) voltage magnitude at i^{th} bus.

ΔV_i^{lim} is the deviation limit of the voltage.

n is the exponent of penalty function and value is (=1)

N_B is the number of buses in the system taken.

W the real non-negative weighting factor and the value is (= 1)

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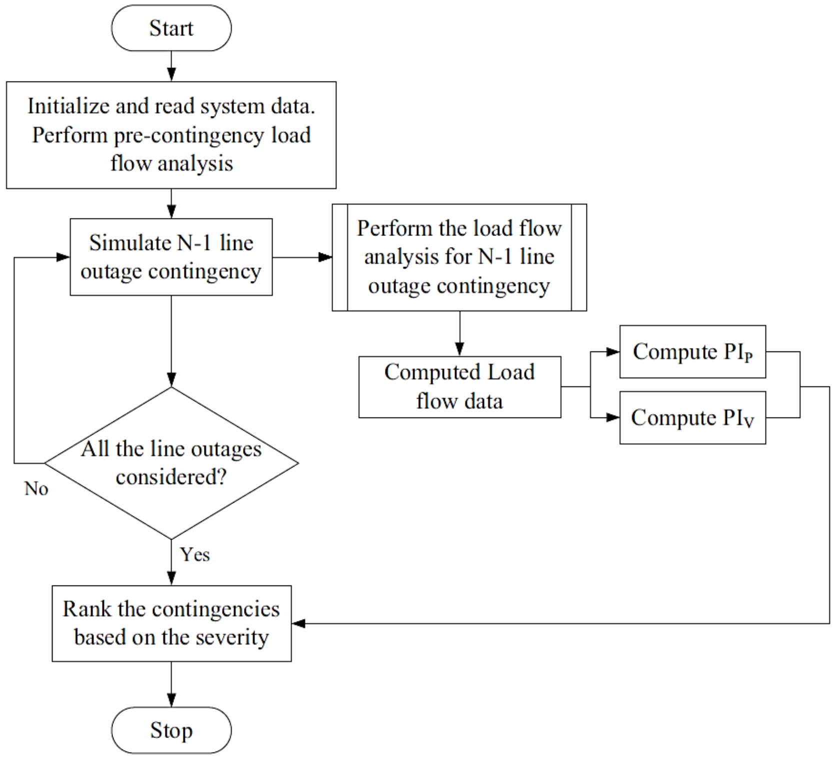

Fig.1. Flow chart for the power system contingency ranking using the NRLF method.

The algorithm for contingency analysis using Newton Raphson load flow solution is as follows:

Step 1: Read the given system's line data and bus data.

Step 2: Without considering the line contingency perform the load flow analysis for base case.

Step 3: Simulating a line outage or line contingency, i.e. removing a line and proceeding to the next step.

Step 4: Load flow analysis is done for this particular outage, then calculation of the active power flow is done in the remaining lines and value P^{max} is found out.

Step 5: The active power performance index (PI_P) is found, which indicates the active power limit

Step 6: subsequently for the particular line contingency; voltages of all the load buses are calculated.

Step 7: Then voltage performance index (PI_V) is being calculated which indicates the voltage limit violation at all the load buses due to the line contingencies.

Step 8: Computation of overall performance index is done by adding PI_P and PI_V for each line outage of the system.

Step 9: Steps 3 to 8 for all line outages is repeated to obtain the PI_P and PI_V for all line outages.

III. ONLINE PSSSA MODULE USING MULTILAYER FEED FORWARD NEURAL NETWORK

TheFigure 2showstheblockdiagramoftherankingmodule.Theinputfeaturesforthe modulecomprises(coveringentireoperatingscenarios)ofactiveandreactivepoweratall theloadbus(P_L,

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Q_L)andgeneratorbuses(P_G, Q_G),thevoltagemagnitudes|V| atallthebuses alongwiththeN-1lineoutagecontingency(K_i).Themodulehastheability topredictthe performance indices to assess the security status by contingency ranking for a given operating condition.ThemoduleusestwoANNarchitectureswhichtakesthelineoutage condition and the loading condition as the inputs a long with other operating conditions and performance indices as the output parameter.The neural network model isused by the module is the MFNN. These two networks are trained for various range of operating condition stop redict the performance indices.

The key functions of the module are that:

(1) It calculates the system severity for each operating condition.

(2) It calculate sseverity indicesunderN-1lineoutage contingency.

(3) The model rank the contingencies based on the irorder of severity.

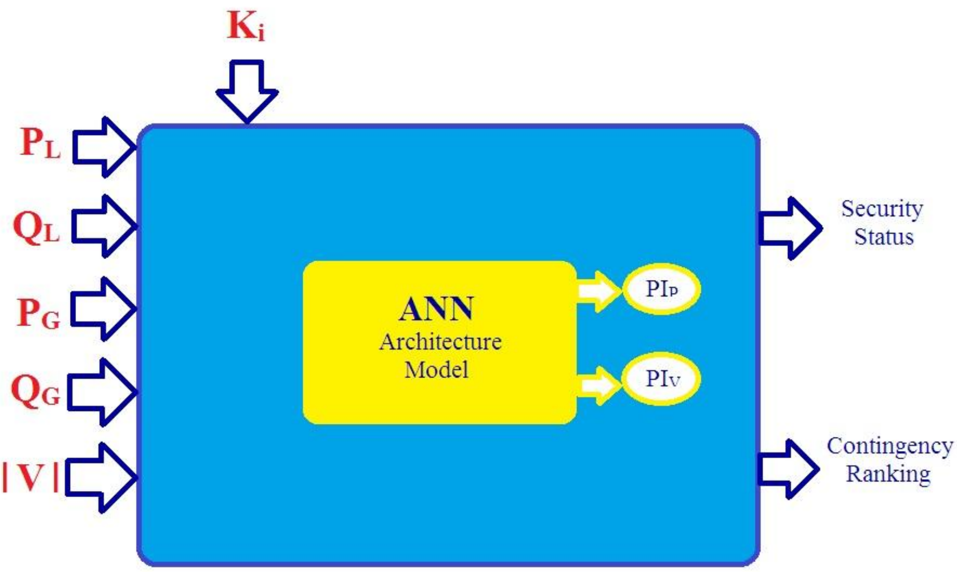

Fig. 2.Architecture of ANN based contingency ranking

IV. MULTI-LAYER FEED FORWARD NETWORK (MFNN)

This paper proposes, MFNN model consisting of three layers, namely input layer, hidden layer and an output layer, with the sigmoidal activation function for all the neurons except for those neurons in the input layer for power system static security assessment.

$$S(x) = \frac{1}{1+e^{-x}} \qquad (4)$$

Each layer is connected with each neuron of the previous layer with weights attached to it. The inputs to the model is the system operating conditions as shown in Fig.3., with performance indices as output.

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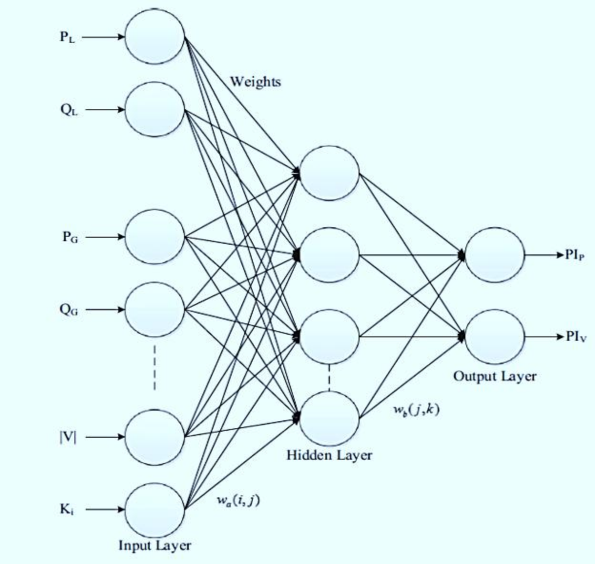

Fig.3. MFNN model for the calculation of performance indices

The MFNN consists of momentum factorα_1, and the learning rate parameter η_1, which have a very crucial effect on the learning rate of the BPA. The BPA contribute an approximation to the trajectory in the weight space calculated by the method of steepest descent. If the considered value of η_1 is very small, which results in slow rate of learning, while if the value of η_1 is too large in order to speed up the rate of learning, the MFNNmay become unstable. A simple method of increasing the rate of learning without making the MFNN unstable is by adding the momentum factor α_1. Preferably, the values of $\eta_1$and $\alpha_1$should lie between 0 and 1.

The weights between the hidden layer and the output layer are updated as in (5);

$w_b(j,k,m+1) = w_b(j,k,m) + \eta_1 * \delta_k(m) * S_b(j) + \alpha_1(w_b(j, k, m) - w_b(j,k,m-1))$(5)

Where j varies from 1 to N_h and k varies from 1 to N_k. Similarly, the weights between the hidden layer and the input layer are updated as in (6);

$w_a(i,j,m+1) = w_b(i, j, m) + \eta_1 * \delta_j(m) * S_a(i) + \alpha_1(w_a(i, j, m) - w_b(i,j,m-1))$(6)

The $\delta_k(m)$ in (5) and $\delta_j(m)$ in (6) are related as in (7);

$\delta_k(m) = \sum_{k=1}^{k} \delta_j(m) * w_b(\mathrm{j, k, m})$(7)

Where i varies from 1 to N_i. The mean square error (MSE) $E_{tr}$for the training patterns after the mth iteration is given as,

$$E_{tr}(m) = \left(\frac{1}{N_p}\right) * \left[\sum_{p=1}^{N_p} \{X_{1p} - X_{2p}(m)\}^2\right] \quad (8)$$

The training is stopped when the least value of $E_{tr}$is obtained and this value does not change much with the number of iterations. The flow chart for above approach is shown in Fig.4.

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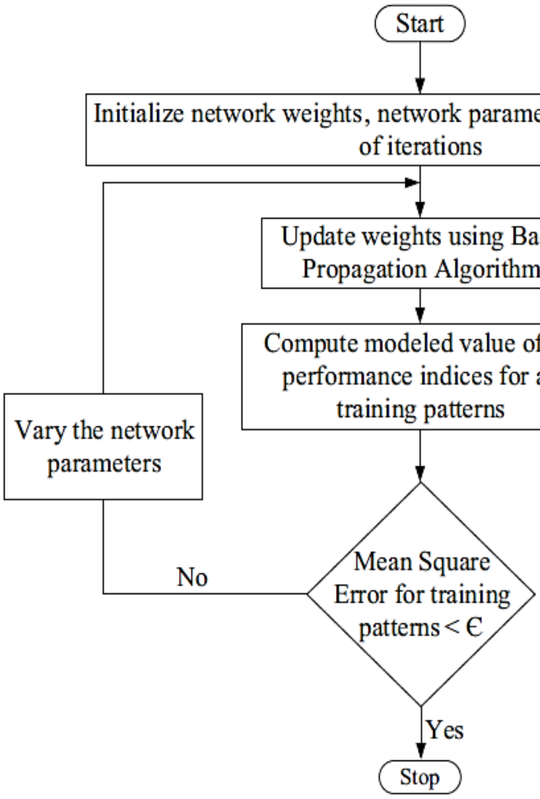

Fig.4. Flow chart for MFNN

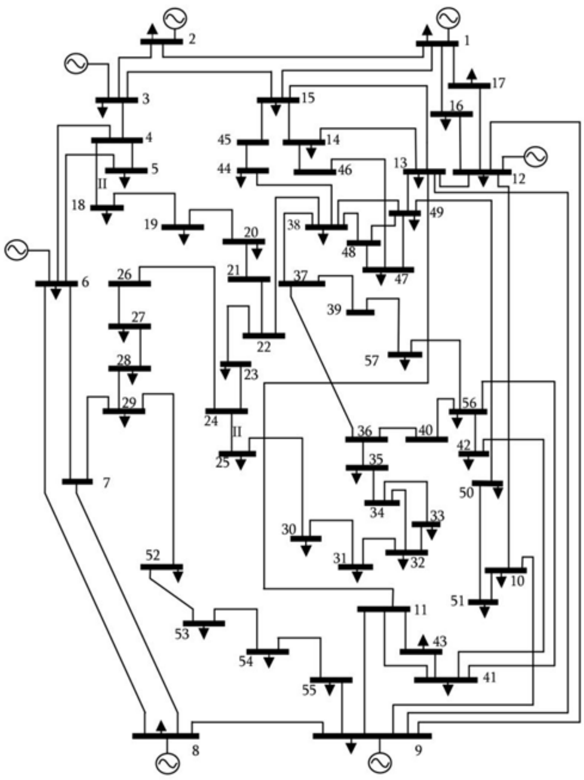

Fig.5. Topology of IEEE 57 Bus system

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Simulation results

Table 1. Contingency ranking of IEEE-57 bus system.

Line outage	Active power PI by NRLF	Active power PI by MFNN	Line Outage	Voltage PI by NRLF	Voltage PI by MFNN
L 4-6	10.7965	10.6519	L 7-29	54.9871	52.5264
L 5-6	9.8042	9.8042	L 37-38	48.9461	48.9458
L 8-9	8.5838	8.5838	L 36-37	26.5853	26.5859
L 7-29	7.1972	7.1972	L 28-29	23.8761	23.8761
L 3-4	6.4139	6.4139	L 4-6	19.4136	19.4139
L 37-38	6.3318	6.3318	L 27-28	14.9879	14.9873
L 36-37	6.2134	6.2134	L 22-38	11.9843	11.9893
L 1-15	6.1615	6.1615	L 1-15	10.8391	10.8385
L 1-17	6.0872	6.0872	L 8-9	10.8382	10.8376
L 28-29	5.8231	5.8231	L 5-6	9.8313	9.8303
L 7-8	5.8192	5.8192	L 46-47	9.7133	9.7124
L 27-28	5.8137	5.8137	L 14-46	9.4376	9.4365
L 1-16	5.7651	5.7651	L 22-23	9.3313	9.3308
L 22-38	5.7281	5.7281	L 26-27	7.5331	7.5328
L 46-47	5.7221	5.7221	L 38-48	6.8442	6.8440
L 14-46	5.7315	5.7315	L 13-49	6.8431	6.8429
L 22-23	5.5310	5.5310	L 7-8	6.8305	6.8302
L 4-18	5.6105	5.6105	L 30-31	6.7018	6.7015
L 14-15	5.5112	5.5112	L 24-26	6.6937	6.6830
L 2-3	5.5016	5.5016	L 1-17	6.5837	6.5868
L 9-55	5.4763	5.4763	L 12-13	6.5861	6.5859
L 41-42	5.4750	5.4750	L 44-45	6.4952	6.4948
L 29-52	5.4631	5.4631	L 15-45	6.3831	6.3829
L 10-51	5.4626	5.4626	L 3-4	5.9152	5.9189
L 11-43	5.4619	5.4619	L 18-19	5.8137	5.8132
L 44-45	5.4531	5.4531	L 47-48	5.7663	5.7661
L 15-45	5.4401	5.4401	L 10-51	5.6241	5.6239
L 38-48	5.3966	5.3966	L 14-15	5.5193	5.5189
L 41-43	5.3951	5.3951	L 38-44	5.4931	5.4929
L 13-49	5.3856	5.3856	L 24-25	5.4852	5.4849
L 52-53	5.3840	5.3840	L 41-42	5.4276	5.4273
L 18-19	5.3718	5.3718	L 24-25	5.3853	5.3849
L 47-48	5.3701	5.3701	L 1-16	5.3637	5.3631

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L 49-50	5.3652	5.3652	L 21-22	5.2597	5.2593
L 38-44	5.3652	5.3652	L 23-24	5.1863	5.1864
L 21-20	5.3551	5.3551	L 11-43	5.1501	5.1506
L 21-22	5.3542	5.3542	L 36-40	4.9943	5.9938
L 6-8	5.3441	5.3441	L 10-12	4.9491	5.9487
L 9-11	5.3415	5.3415	L 4-48	4.9376	5.9373
L 56-41	5.3412	5.3412	L 21-20	4.9181	4.9179
L 13-15	5.3387	5.3387	L 13-15	4.8881	4.8876
L 9-10	5.3321	5.3321	L 38-49	4.8721	4.8719
L 31-32	5.3216	5.3216	L 12-17	4.8097	4.8094
L 24-26	5.3066	5.3066	L 41-43	4.7918	4.7914
L 26-27	5.3066	5.3066	L 52-53	4.7801	4.7789
L 24-25	5.2934	5.2934	L 50-51	4.7731	4.7329
L 12-13	5.2915	5.2915	L 9-10	4.7321	4.7318
L 6-7	5.2910	5.2910	L 31-32	4.7208	4.7206
L 54-55	5.2901	5.2901	L 29-52	4.7113	4.7109
L 30-31	5.2893	5.2893	L 4-18	4.6918	4.6914
L 48-49	5.2876	5.2876	L 11-4	4.6837	4.6831
L 11-13	5.2853	5.2853	L 13-14	4.6813	4.6809
L 23-24	5.2853	5.2853	L 2-3	4.6710	4.6704
L 37-39	5.2839	5.2839	L 37-39	4.6370	4.6367
L 39-57	5.2835	5.2835	L 9-11	4.6342	4.6338
L 56-42	5.2822	5.2822	L 49-50	4.6118	4.6117
L 57-56	5.2819	5.2819	L 56-41	4.5986	4.5983
L 9-13	5.2813	5.2813	L 54-55	4.5977	4.5973
L 12-17	5.2791	5.2791	L 9-55	4.9534	4.5927
L 19-20	5.2780	5.2780	L 6-8	4.5418	4.5413
L 13-14	5.2755	5.2755	L 48-49	4.5393	4.5391
L 12-16	5.2741	5.2741	L 53-54	4.5816	4.5182
L 38-49	5.2738	5.2738	L 57-56	4.5094	4.5090
L 10-12	5.2729	5.2729	L 3-15	4.4996	4.4991
L 24-25	5.2719	5.2719	L 56-42	4.4873	4.4871
L 9-12	5.2714	5.2714	L 9-13	4.4239	4.4138
L 4-18	5.2698	5.2698	L 11-13	4.4016	4.3914
L 3-15	5.2665	5.2665	L 12-16	4.3998	4.3896
L 11-4	5.2635	5.2635	L 19-20	4.3973	4.3868
L 40-56	5.2621	5.2621	L 9-12	4.3762	4.3658

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L 36-40	5.2539	5.2539	L 6-7	4.3518	4.3416
L 53-54	5.2534	5.2534	L 39-57	4.3216	4.3109
L 50-51	5.2435	5.2435	L 40-56	4.3096	4.2914

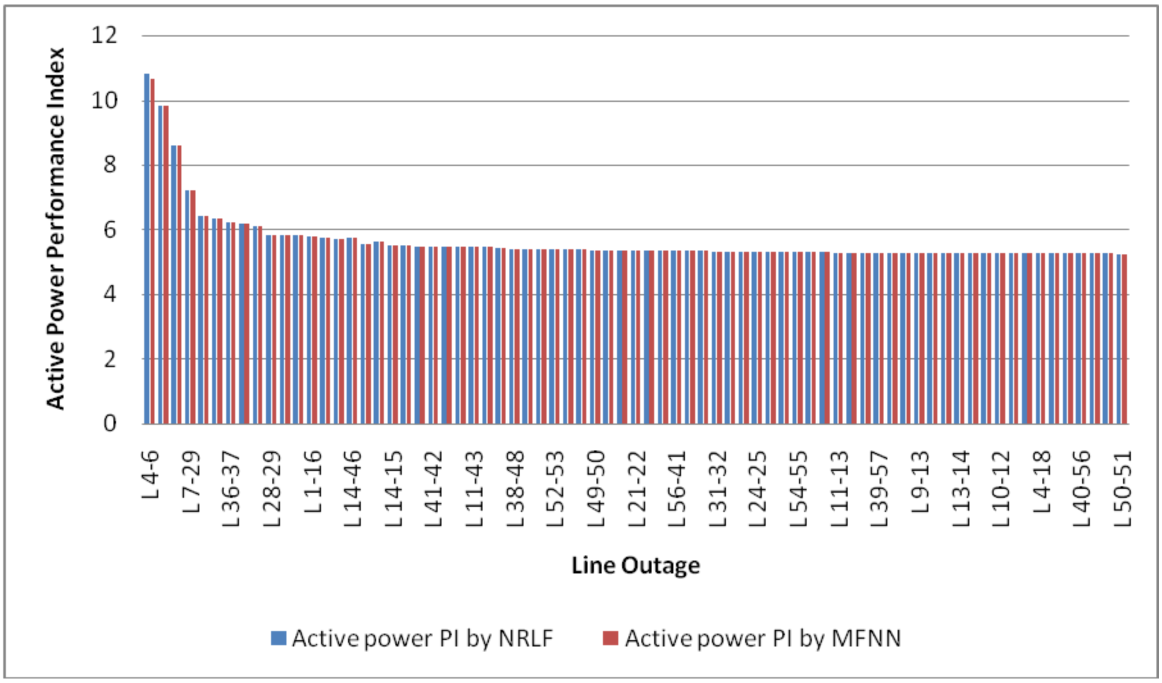

Fig.5. Comparison of Active Power Performance Index and Contingency Ranking.

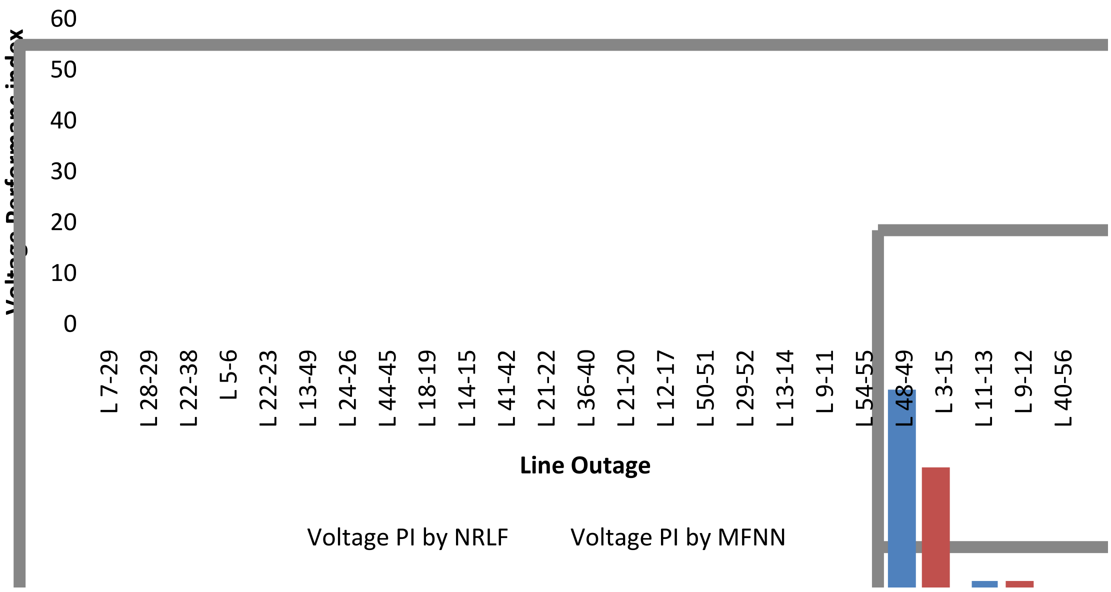

Fig.6. Comparison of voltage performance Index and contingency ranking.

V. CONCLUSION

Performanceindicesandcontingencyrankingforthebasecase loadcondition for IEEE 57 Bus System is shown inTable1.The1st and4th columnsoft h e tableshowthe variouslineoutages.2ndand5thcolumns of the table 1shows rank based on severity using active power performance index and voltage performance index computed using NRLF analysis. The 3rd and 6th columns of the Table1 shows the active power and voltage performance indices values obtained using the MFNN model. It can be observed that for all the critical contingencies, the predicted values and ranking are almost equal by the module using MFNN model in comparison with columns 2and5 respectively. Here, the top critical contingencies need to be given higher priority during security evaluation. Further, the time taken by the model is found to be1.49sec (IEEE-57 bus system)for 100iterations.So, the ranking module for security assessment by contingency ranking is very quick and accurate for unseen system conditions. From the simulation results and above discussion, for various system operating conditions, the ranking module using MFNN is found to be quick and efficient approach to predict the performance indices and rank the contingencies. Thus, this MFNN ranking module is found feasible for online implementation for security assessment by contingency ranking.

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