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Abstract

Vulnerability prediction of power systems is important so as to determine its ability to continue to provide service in case of any unforeseen catastrophic contingency. It is considered one of the vital concerns due to the continual blackouts in recent years which indicate that the power system today is too vulnerable to withstand a severer disturbance. The objective of this paper is to investigate and compare the performance of two vulnerability indices used for assessing the vulnerability of power systems when subjected to various contingencies. The Probabilistic Neural Network (PNN) based on power system loss and possible loss of load will be used to speed up the assessment technique. In this study, contingency analyses were carried out on a practical 87 bus test system and the vulnerability indices were calculated using the MATLAB program. Results presented show that PSL index is more accurate for analyzing the impact of contingencies on a practical power system from the view point of power system loss considering the loss of power during contingencies.

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Probabilistic Neural Network for Vulnerability Prediction on a Practical Power System

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Abstract—**Vulnerability prediction of power systems is important so as to determine its ability to continue to provide service in case of any unforeseen catastrophic contingency. It is considered one of the vital concerns due to the continual blackouts in recent years which indicate that the power system today is too vulnerable to withstand a severer disturbance. The objective of this paper is to investigate and compare the performance of two vulnerability indices used for assessing the vulnerability of power systems when subjected to various contingencies. The Probabilistic Neural Network (PNN) based on power system loss and possible loss of load will be used to speed up the assessment technique. In this study, contingency analyses were carried out on a practical 87 bus test system and the vulnerability indices were calculated using the MATLAB program. Results presented show that PSL index is more accurate for analyzing the impact of contingencies on a practical power system from the view point of power system loss considering the loss of power during contingencies.**

Keywords-Electrical power system; Probabilistic Neural Network; Vulnerability indices; Contingency analysis

I. INTRODUCTION

The rapid development of economy and the deregulation of power industry increase the demand of power supply and grow the complexity of power grid. Since September 11, 2001 the security of major national infrastructures has become a critical concern to government and industry of any country. Power system is responsible for the continuous power supply but when some unpredicted disasters happen, especially earthquake, flood or terrorism attacks, operators have to guarantee the safety of the main part of the system and the power supply of some important infrastructures, such as transportation, communication etc. So vulnerability prediction is made by assessing system conditions for credible contingencies, and how they are affected by the changes in a critical system parameter [1].

The threat of terrorist attack has risen as a big threat to many areas of economy. Almost every economic and social function is based in some way on the sourcing of energy, telecommunication services, transportation, etc. An attack to these infrastructures would bring devastating effects on the economy and in the people's life. In power systems, the target can be the electric infrastructure for example, terrorists could attack simultaneously two substations or key transmission towers in order to cause a black out in a big area of the grid [2,3]. Similarly, the earthquake and flood may result in catastrophic of more than one power station, main substation or transmission line. Therefore, the goal of vulnerability prediction is to combines information on the level of system security and its trend with changing system condition as well as information on a wide range of scenarios, events and contingencies with regards to which a system is vulnerable.

The threats of terrorism attacks, earthquake and flood are not considered in security prediction of power system which includes transient stability prediction and voltage collapse prediction. Thus, Power system vulnerability prediction covers almost all aspects of power system and it requires analysis of the system behavior under a prescribed set of events known as contingencies such as line outage, generator outage, increase in total load and amount of load disconnected [4]. Recent papers have addressed power system vulnerability prediction in terms of developing vulnerability indices so as to reflect the level of system weakness relative to the occurrence of an undesired event [5]. Some examples of vulnerability indices were that based on adequacy indices which consider bus isolation probability [6], anticipated loss of load [1] and possible loss of load [4]. However, because the vulnerability index of the system is just the weighted sum of the individual component's index and the influence of the individual part only indicated by the weight value and therefore may not represent the actual state of the system. The better way to do is to focus on some problems specifically and solve them with different methods [4].

Accurate vulnerability prediction is very important and fast intelligent technique based on vulnerability index (VI) is significantly needed to determine how vulnerable a current power system is so that preventive and emergency control steps can be taken to minimize catastrophic power outages and reduce the associated risk and steer the system to viable conditions. Presently, the use of Artificial Neural Network (ANN) in vulnerability prediction and to solve other power system problems has gained a lot of interest among researchers due to its ability to do parallel data processing, high accuracy and fast response [7 – 11].

This paper introduces a performance comparison of vulnerability indices based on power system loss [12] and possible loss of load [4] in which the Probabilistic Neural Network is used for fast detection. In Section II and III, the descriptions of vulnerability indices are provided. In Section

IV, PNN implementation for vulnerability prediction is outlined. Numerical test results are presented in Section V. Conclusion is given in Section VI.

II. VULNERABILITY INDEX BASED ON POWER SYSTEM LOSS

The vulnerability index based on power system loss (PSL) considers total system loss, generation loss due to generation outage, power line loss due to line outage, increase in total load and amount of load disconnected. The rational for considering PSL is due to the fact that losses in a power transmission system are a function of not only the system load but also of the generation. In addition, each contingency has an effect not only on the system performance but also on power losses in the system. The outage of transmission line, transformer or generator may result in overload of other lines and causes increased active power loss in transmission lines and reactive power loss in transformers. Similar effect may result if a contingency such as loss of load is said to occur. Therefore, it is important to consider total power system loss as a measure for indicating vulnerability of power systems [8].

The formulation of the PSL index is given by,

$$PSL=\frac{S_{BCL}}{S_{CCL}+S_{LI}+S_{DL}+\sum_{i=1}^{n}S_{LGO,i}W_{G,i}+\sum_{i=1}^{m}S_{LLO,i}W_{L,i}} \qquad (1)$$

where,

S_{BCL} : system power loss in MVA at base case

S_{CCL} : system power loss in MVA at contingency case

S_{LI} : increase in total load in MVA

S_{DL} : amount of load disconnected in MVA

$S_{LGO,i}$: loss of generated MVA due to generator outage

$S_{LLO,i}$: loss of transported MVA due to line outage

$W_{G,i}$: weight of individual generator power output

$W_{L,i}$: weight of individual line power influence

n : number of generators

m : number of lines

From equation (1), it can be noted that the vulnerability index, PSL will have values in the range of 1 – 0 assuming that at a contingency case, the losses in a power system will be greater than at base case. These values can be categorized by a control operator based on its vulnerability boundaries. If the value of PSL is close to 1.0, it indicates that the system is 'Invulnerable' whereas if the PSL value is small, that is, close to 0, it implies that the system is 'Vulnerable'. The assumed limits of index values can be changed or readjusted by a control operator based on any new system configuration. The weight of individual generator and line are chosen based on their importance considering power system operating practices [8].

III. VULNERABILITY INDEX BASED ON POSSIBLE LOSS OF LOAD

The vulnerability index based on possible loss of load (PLL) takes into consideration the fact that if unpredicted natural disasters happen which may be due to earthquake or flood, operators will need to shed some load to guarantee the safety of the main parts of a power system and supply power to some important infrastructures. So the structural vulnerability of a power grid is defined as possible loss of load due to the amount of load shed [4]. Thus, the PLL index is the ratio of loss of load in a system which is given by,

$$PLL=\frac{\sum_{i}^{n}S_{shed}}{S_{\sum}} \qquad (2)$$

where,

S_{shed} : amount of load shed at the i^{th} bus in MVA

$S_{\sum}$: total system load in MVA

The PLL index is considered similar to the ALL index which is based on the amount of load shed that may be lost due to a contingency in order to avoid a cascading outage [1]. If more load is shed, it means that a power system becomes more vulnerable and therefore the system is said to be less capable of resisting emergencies. PLL is used to assess vulnerability of power systems based on the fact that if the PLL value is greater than the value at base case, it indicates that the system is vulnerable [5].

IV. PNN IMPLEMENTATION FOR OR VULNERABILITY PREDICTION ON A PRACTICAL POWER SYSTEM

PNN which is a class of Radial Basis Function network is useful for automatic pattern recognition, nonlinear mapping and estimation of probabilities of class membership and likelihood ratios. It is a direct continuation of the work on Bayes classifiers in which it is interpreted as a function that approximates the probability density of the underlying example distribution. The PNN consists of nodes with four layers namely input, pattern, summation and output layers as shown in Fig. 1. The input layer consists of merely distribution units that give similar values to the entire pattern layer. For this work, RBF is used as the activation function in the pattern layer and the inputs are the active and reactive power flows and power generations. Fig. 2 shows the pattern layer of the PNN [7,13]. The $\|dist\|$ box shown in Fig. 2 subtracts the input weights, $IW_{1.1}$, from the input vector, p and sums the squares of the differences to find the Euclidean distance. The differences indicate how close the input is to the vectors of the training set. These elements are multiplied element by element, with the bias, b, using the dot product (.*) function and sent to the radial basis transfer function. The output a is given as,

$$a = radbas(\|IW_{1.1} - P\|b) \tag{3}$$

where, radbas is the radial basis activation function which can be written in general form as,

$$radbas(n) = e^{n^2} \tag{4}$$

The training algorithm used to train the RBF is the orthogonal least squares method which provides a systematic approach to the selection of RBF centers. The summation layer shown in Fig. 1 simply sums the inputs from the pattern layer which correspond to the category from which the training patterns are selected as either class 1 or class 2. Finally, the output layer of the PNN is a binary neuron that produces the classification decision. As for this work, the classification is either class 1 for secure system class 2 for insecure system.

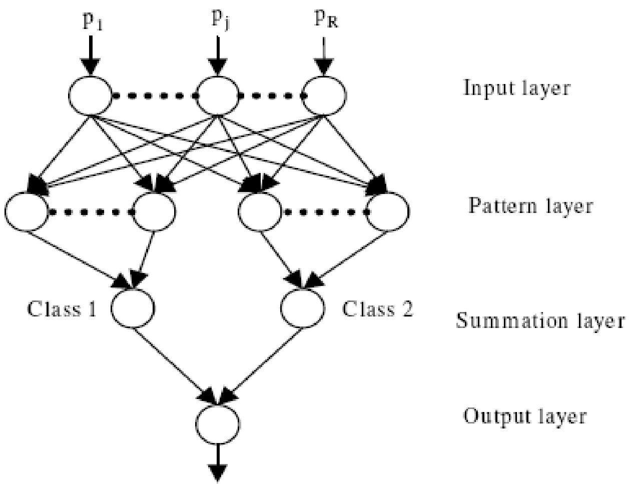

Figure 1. PNN architecture

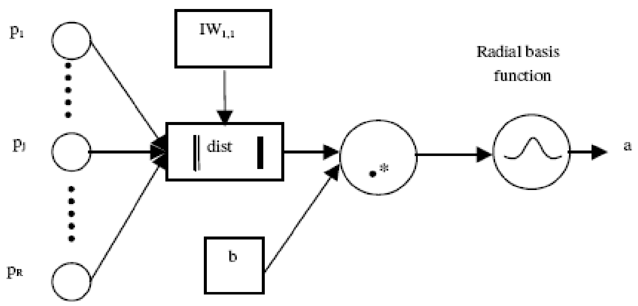

Figure 2. PNN pattern layer

The procedures involved in power system vulnerability prediction using PNN are:

- Analyzing the system behavior at the base case condition.
- Analyzing the system behavior when subjected to credible system contingencies such as line outage (LO), generator outage (GO), load increase (LI) and disconnection of loads (DL).
- At each contingency case, the vulnerability indices are calculated.
- The inputs data are proceed into the PNN and the outputs (PSL and PLL) from the PNN are then compared with each other so as to determine the effectiveness and accuracy in assessing vulnerability of power systems.

In this study, simulations were carried out on a practical 87 bus test system shown in Fig. 3. For the calculation of the vulnerability indices, the weights of all the system parameters are set equal to 1.0 for simplicity. In practice, system operators may assign different weights to represent the varying importance of selected elements in the system.

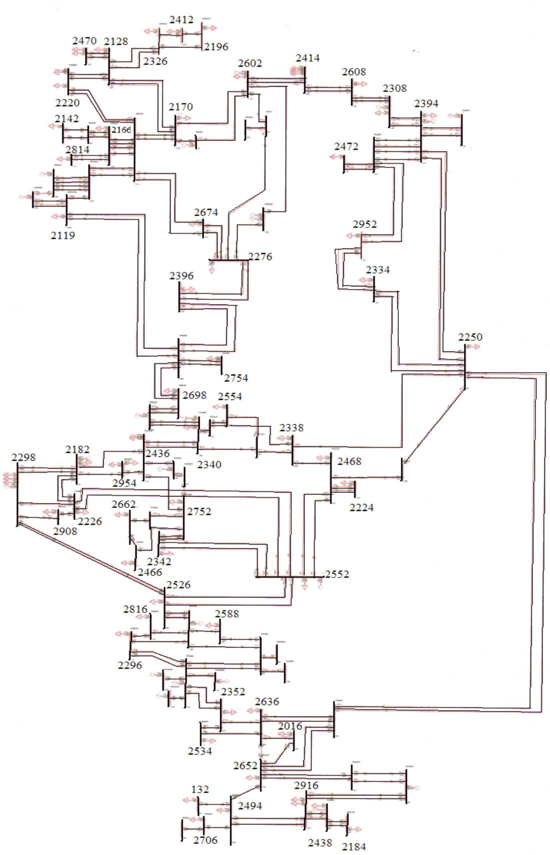

Figure 3. Single line diagram of a practical power system

V. Results And Discussion

The PSL index is used for vulnerability prediction on the 87 bus test system and its performance is compared with the vulnerability index PLL. The PLL index is the ratio of loss of load in a system due to a contingency. The more load the system loses after a contingency, the more vulnerable the system is, and less capable the system is of resisting emergencies. The criteria for determining system vulnerability is based on the vulnerability index calculated at base case in which a system is said to be invulnerable if the PSL value is close to 1.0 and the PLL value is close to 0.0.

The results of the vulnerability indices, PSL and PLL calculated at each contingency case are summarized as shown in Table 1 and also shown graphically as in Figs. 4 and 5. From Table 1, it can be seen that the system is close to vulnerability for most of the contingencies except for outage of lines; LO-12(2016-2652), LO-74(2250-2338), LO-75(2250-2339), LO-81(2276-2396) and LO-132(2420-2652) because the PSL and PLL values are close to the base case values of 1.0 and 0.0, respectively.

Comparing the results of PSL and PLL indices in terms of contingencies that cause system to be vulnerable and invulnerable, it is noted from Fig. 5 that some of the contingencies give comparatively high values of PLL such as contingencies due to multiple outage of generators 2436 and 2684 (GO-2436,2684), multiple outage of generators 2182,2298 and 2436 (GO-2182,2298,2436), multiple outage of lines 104 and 105 (LO-104,105) and increase in total load LI-20%, LI-25% and LI-30%. Referring to Fig. 4, these contingencies are recognized by PSL indices as vulnerable because the indices values are close to 0 and such values have been classified as causing the system vulnerable. If such contingencies occur, the system is said to be vulnerable and may cause interruption of power supply.

From Table 1, it is noted that for some of contingency cases, the PLL index does not give a clear prediction about the vulnerability of the system such as multiple outage of lines 89 and 90 (LO-89,90), multiple outage of lines 102,103 and 136 (LO-102,103,136), multiple outage of lines 4,7,150 and 151 (LO-4,7,150,151), multiple outage of lines 106,107,150 and 151 (LO-106,107,150,151) and 108,109,146 and 147 (LO-108,109,146,147) and multiple outage of lines 69,70,106,107,150 and 151 (LO-69,70,106,107,150,151) because the PLL values for these contingency cases are close to 0 which indicates that the system is invulnerable. However, these contingencies are classified by PSL index as making the system alert (close to vulnerability). It is also noted that these contingency cases result in low voltage magnitudes at the system buses and therefore such condition makes the system to be in an alert state.

Based on the vulnerability index in terms of power system loss PSL, It can be concluded that vulnerability of a power system can be assessed. Thus, the PNN can be a useful tool for providing a fast and accurate vulnerability prediction of power systems.

TABLE I. Vulnerability Indices at Various Contingency Cases

Contingency cases	PSL	PLL
Base Case	1.0	0.0
LI-10%	0.55777	0.14858
LI-15%	0.26851	0.24529
LI-20%	0.15908	0.36612
LI-25%	0.10316	0.52362
LI-30%	0.06924	0.74239
LO-12(2016-2652)#	0.98312#	0.00003#
LO-74(2250-2338)#	0.89805#	0.00002#
LO-75(2250-2339)#	0.81762#	0.00009#
LO-81(2276-2396)#	0.8903#	0.00009#
LO-132(2420-2652)#	0.91285#	0.00006#
LO-21,22	0.43615	0.01617
LO-35,36	0.17784	0.10563
LO-89,90♦	0.47528	0.00175♦
LO-78,79	0.47393	0.02584
LO-98,99	0.55261	0.01683
LO-104,105	0.08513	0.29167
LO-110,111	0.17902	0.0589
LO-165,166	0.4685	0.02253
LO-75,78,79	0.33075	0.0387
LO-102,103,136♦	0.54824	0.00294♦
LO-72,73,76,77	0.14399	0.12805
LO-74,75,78,79	0.16177	0.11297
LO-21,22,33,34	0.09787	0.23577
LO-21,22,81,82	0.09756	0.2367
LO-4,7,150,151♦	0.41043	0.0067♦
LO-78,79,89,90	0.31131	0.04494
LO-89,90,159,160	0.31131	0.04494
LO-106,107,150,151♦	0.51373	0.0022♦
LO-108,109,146,147♦	0.58724	0.00095♦
LO-114,115,116,117	0.44425	0.02434
LO-69,70,106,107,150,151♦	0.38835	0.00284♦
GO-2684	0.54187	0.02005
GO-2182,2436	0.11595	0.15005
GO-2424,2438	0.44656	0.02445
GO-2436,2684	0.06143	0.38062
GO-2510,2511	0.29881	0.02009
GO-2552,2740	0.24656	0.05625
GO-2182,2298,2436	0.06244	0.35961
GO-2182,2298,2684	0.12182	0.12993
GO-2182,2298,2740	0.1142	0.14439
GO-2308,2394,2638	0.19572	0.06004
GO-2510,2511,2158,2306	0.25938	0.02403
GO-2182,2298,2552,2740	0.08656	0.21578
GO-2298,2410,2424,2552	0.12151	0.13225
GO-2298,2410,2438,2552	0.112	0.14702
GO-2298,2410,2424,2438,2552	0.09558	0.16849
GO-2410,2464,3184,3185,3186	0.13264	0.13526
GO-2424,2464,3184,3185,3186	0.16145	0.10466
GO-2438,2464,3186,3184,3185	0.1464	0.11775

Invulnerable Case, ♦ Not Clear Prediction

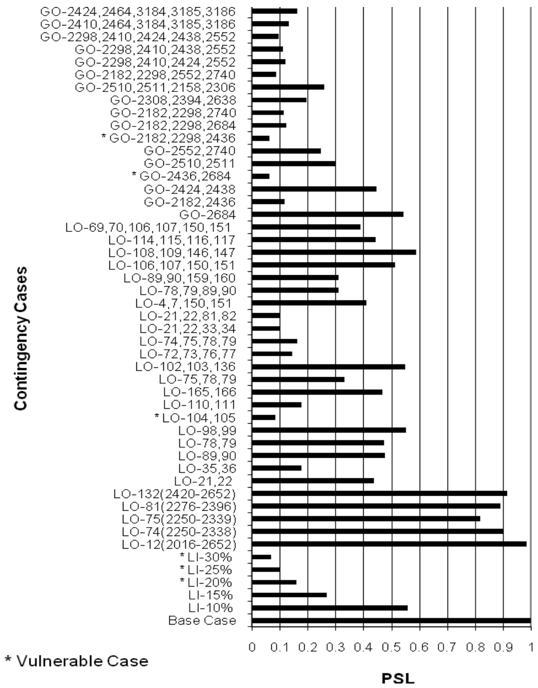

Figure 4. Vulnerability indices based on PSL

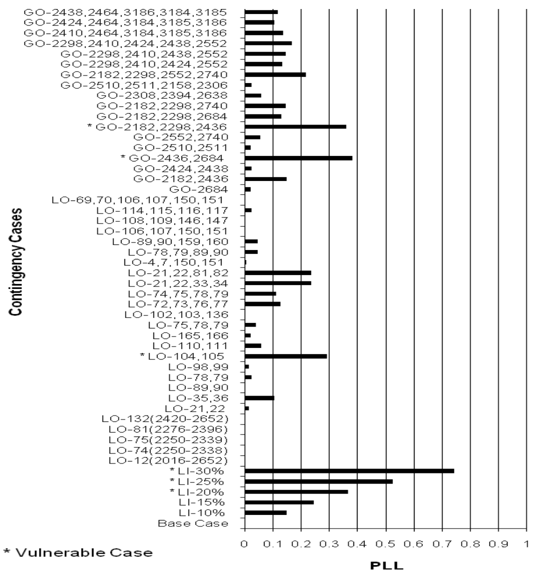

Figure 5. Venerability indices based on PL

VI. CONCLUSION

The paper presented a performance comparison of vulnerability indices PSL and PLL using PNN as a fast detection for vulnerability of a power system when subjected to various contingencies. The concept behind the indices is given and used in the formulation of the PSL and PLL. Test results demonstrated that the PSL index was more accurate in assessing the vulnerability of power system when compared with the PLL index because it gave a clearer prediction about the status of power system vulnerability in which the system can be classified as invulnerable, alert vulnerable and vulnerable based on the PSL values in the range of 0 to 1.0. Such vulnerability index can determine how vulnerable a power system is, so that preventive and emergency control steps can be taken to minimize catastrophic power outages. The use of PNN based on PSL to determine the vulnerability can help system operators to take quick control actions so as to avoid any cascading outage.

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