The Classification of Power Swing Based on PNN and MLPNN

Ahmad Farid Bin Abidin[*1], Azah Mohamed[2], Hussein Shareef[3]

[1]Center for Power Engineering Studies, Faculty of Electrical Engineering
Universiti Teknologi MARA, Shah Alam, 40450, Selangor, Malaysia

[2, 3]Department of Electrical, Electronic and Systems Engineering
Universiti Kebangsaan Malaysia, Bangi, 43600, Selangor, Malaysia

[*1]ahmad924@salam.uitm.edu.my; [2]azah@eng.ukm.my; [3]shareef@eng.ukm.my

***Abstract*-An intelligent approach is developed to discriminate a fault, stable swing and unstable swing for correct distance relay operation by using the S-transform and the probabilistic neural network (PNN). To illustrate the effectiveness of the proposed techniques, simulations were carried out on the IEEE 39 bus and a practical test system using the PSS/E and MATLAB software. Test results show that the PNN gives an overall classification accuracy of 97.33% in which it performs better than MLPNN in detecting and classifying unstable swing, stable swing, fault, fault clearance and post fault events. Such fast and accurate intelligent detection schemes are useful for preventing distance relay from tripping during power swing.**

***Keywords- Unstable Swing; Stable Swing; S-transform; Probabilistic Neural Network (PNN);* Multi Layer Perceptron Neural Network (MLPNN)**

I. INTRODUCTION

Power systems are large interconnected nonlinear systems where system wide instabilities can occur when the system is subjected to sudden events as the loss or application of large blocks of load, line switching, generator disconnection and faults [1]. The ever increasing load demand and the deregulated power market recently pushed the power system to operate close to its stability limits which makes the system vulnerable to wide area instabilities or collapses, and finally cascading blackout that can affect millions of people and cause huge economic loss [2-3]. Cascading blackouts can be initiated due to many reasons and one of the prominent causes of such event is unintended operation of distance relays [4].

Currently, distance protection with respect to transient instability is one of the critical issues in transmission systems. The conventional zone 3 distance protection relays on transmission lines may not be able to distinguish between voltage instability and short circuit faults [5]. This situation can lead to undesired operation of relays and as a consequence, the system can be exposed to voltage collapse.

Power swings or oscillations occur following a system disturbance such as load change or fault clearance. Power swing has been identified as one of major causes that bring a power system to a major blackout as reported in [6-7]. When a power swing occurs, the measured impedance can enter the relay stripping zone to initiate tripping signals of associated breakers [8]. A change appears in the relative phase angle between two groups of generators and as a consequence, the measured voltage, current, apparent impedance, active power, reactive power and angle vary due to oscillations during power swing [9]. From the aforementioned electrical quantities, many techniques have been developed to prevent relay tripping during a power swing [10-14].

Apostolov et al. [15] has introduced a superimposed component which is proven to be a very formidable tool for power swing detection. A major advantage of the superimposed component based on faulted phase selection method is that it does not require any settings and is not significantly affected by the magnitude of the pre-fault load current. It also works very well under evolving fault conditions. However, the technique seems to be computationally inefficient as the computation process requires three phase sinusoidal currents to differentiate a fault and a power swing.

Jiao et al. [11] has used a combination of the swing center’s voltage waveform and synthetic negative sequence vector to differentiate between a fault and a power swing. The technique seems to be rigorous in discriminating power swing and high fault resistance for protection purposes. However, it requires demanding computation of derivative operation for the swing center’s voltage waveform. There is also a time delay of about 30-40 ms before a fault and a swing can be identified and hence the method is relatively slow as compared to the technique proposed by Jonsson & Dalder [10]. Su et al. [12] has developed a technique based on $V\cos\theta$ which activated a power swing detector in about 30-50 ms. The technique, however, requires further testing in large power systems before it can be deployed to a relay. Xiangning et al. [13] used the derivatives of real and reactive powers to develop an unblocking scheme for distance protection during symmetrical faults in power systems. The unblocking scheme sends the trip signals after 30 ms in the event of a fault. This technique is considered complicated and computationally inefficient because it requires instantaneous product of voltage, current and angle to obtain the real and reactive powers. A more advanced technique using adaptive neuro fuzzy system has been developed to block the relay trip signals during power swings [14]. However, the technique has not been validated on the zone 3 relay operation setting considering that this zone is the most vulnerable zone during power swings. In addition, the relay response time is greater than 40 ms which is very slow as compared to other techniques developed in [10], [12-13]. A very fast and reliable swing detector has been proposed by Afzali and Esmaeilian [16] and Mahamedi and Zhu [17]. However, both techniques were not able to distinguish the stable and unstable swing.

Pang *et al.* [18] has introduced the use of wavelet transform (WT) to detect the power swing occurrence in power system. The method extracts the travelling waves from transient signals induced by faults and calculates the energy of high frequency components extracted using wavelet transform. An approach which is based on Fast Fourier Transform (FFT) for power swing detecting scheme is presented by Mahamedi [19]. This technique is based on the detection of frequency component of the three-phase active power. It is demonstrated that during power swings the frequency of the three-phase active power is equal to slip frequency, whereas after symmetrical fault inception time the frequency of the three-phase active power equals to 50Hz. Nonetheless, both techniques have never been tested for unstable swing condition.

From the literature, the existing techniques are considerably slow and could trigger false relay operation during fast power swing and fault clearance operation at the adjacent line. Hence, it is important to develop a fast and rigorous approach for detecting a fault, fault clearance operation of a circuit breaker at an adjacent line, stable power swing and unstable to prevent undesirable distance relay operation. Due to the promising performance of AI techniques in various power system applications, these techniques are employed for more accurate and selective operation of distance relays. To address the need for fast detection of unstable swings so as to improve the reliability of distance relay operation, a new scheme for detecting a fault, stable swing and unstable swing at transmission lines is proposed by using the S-transform and PNN. Here, the PNN is used because it is considered as an effective tool for solving many classification problems.

II. INTELLIGENT TECHNIQUES FOR PREVENTING DISTANCE RELAY OPERATION DURING POWER SWING

The S-transform which is an advanced signal processing technique and artificial neural network techniques such as the PNN and the multi-layer perceptron neural network (MLPNN) are applied for detecting stable swing, unstable swing and fault in distance relay operation. The background theories of the MLPNN, PNN and SVM are first presented and then followed by its implementation in the distance relay operation.

A. Multilayer Perceptron Neural Network and Probabilistic Neural Network

The MLPNN is a feedforward neural network with one or more hidden layers [20]. A typical configuration of the network consists of an input layer, one or more hidden layers and an output layer. An MLPNN with one hidden layer is shown in Fig. 1.

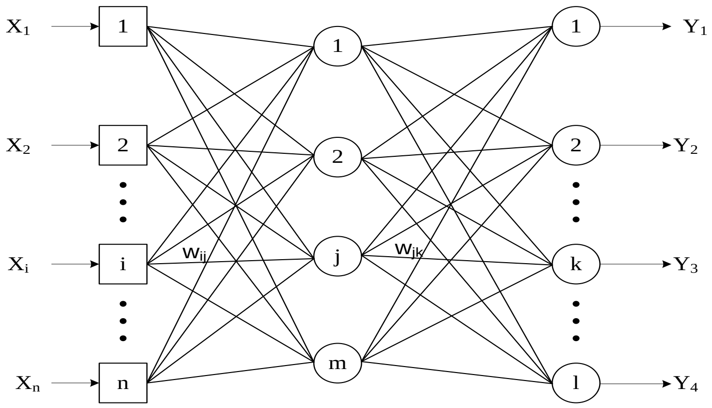

Fig. 1 Topological structure of MLPNN

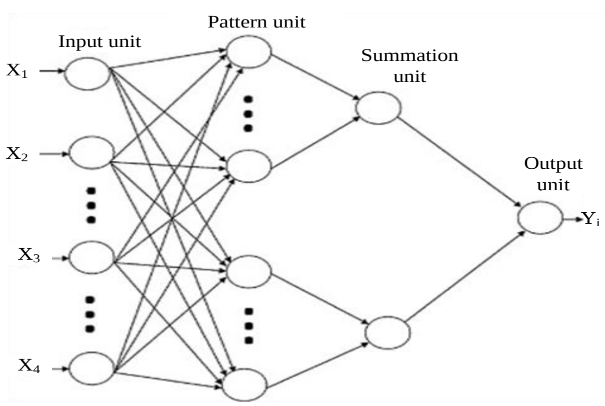

Fig. 2 The topological structure of PNN

The input layer accepts the input signals and redistributes these signals to all the neurons in the hidden layer. In order to determine the output of the neurons, a net weighted output is computed and passed through an activation function.

The probabilistic neural network (PNN) is a kind of radial basis network suitable for solving classification problems [21]. It uses kernel-based approximation to form an estimate of the probability density functions of classes in a classification task [22]. The PNN architecture is composed of many interconnected processing units or neurons organized in successive layers. The topological structure of PNN which comprises of four layers with one input layer, two hidden layers and one output layer is shown in Fig. 2.

B. Classification of Three Phase Fault, Stable and Unstable Swings Using

To address the need for fast detection of unstable swings so as to improve the reliability of distance relay operation, a new scheme for detecting a fault, stable swing and unstable swing at transmission lines is proposed by using the S-transform and artificial neural networks. The S-transform is used to extract features of signals obtained during a fault, stable swing and unstable swing whereas artificial neural networks based on MLPNN and PNN are used to classify either a fault, stable swing or unstable swing for correct distance relay operation as shown in Fig. 3. During a stable swing, it is compulsory to block the tripping signals, while for unstable swing the tripping signals have to be triggered to the associated breaker for isolation purposes.

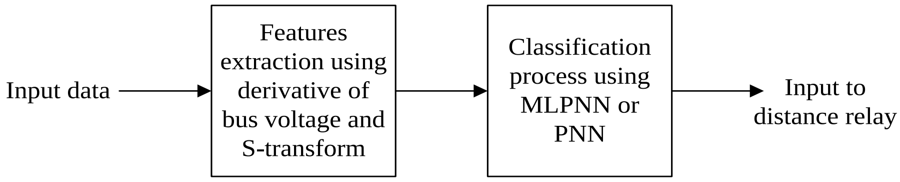

Fig. 3 Automated detection of three phase fault, stable and unstable swings using the S-transform, MLPNN and PNN

C. S-Transform as Feature Extraction Approach

As for the detection of an unstable swing, a fast tripping action needs to be triggered at transfer line to the associated breaker for isolation purposes. S-transform is a time-frequency representation known for its local spectral phase properties. A key feature of the S-transform is its accurate time-frequency (amplitude and phase) domain by employing a moving and scalable localizing Gaussian window [23]. The basis function for the S-transform is the Gaussian modulated cosine wave whose width varies inversely with frequency.

The S-transform of a discrete time series is given by

$$S\left[kT, \frac{n}{NT}\right] = \sum_{m=0}^{m=N-1} H\left[\frac{m+n}{NT}\right] e^{\frac{2\pi^2 m^2}{n^2}} e^{-2\pi mk}, n \neq 0 \tag{1}$$

where,

k, m, n =0,1,...., N -1

T: sampling interval

N: total of sampling point

Equation (1) can be further simplified as

$$S\left[kT, \frac{n}{NT}\right] = \sum_{m=0}^{m=N-1} H\left[\frac{m+n}{NT}\right] \Phi^{\left(\frac{m}{n}\right)^2} \Gamma^{\frac{mk}{n}}, n \neq 0 \tag{2}$$

where,

$$\Phi = e^{-2\pi^2} \text{ and } \Gamma = e^{j2\pi}$$

Proper selection of input features is an important step before implementing the PNN and MLPNN. The input features of the MLPNN and PNN are selected by considering the derivative of bus voltage, the bus voltage and bus active power processed by the S-transform. The mathematical formulation of the input features is described accordingly.

The first feature, *F1*, is given by,

$$F1 = \rho + 1, if \ \frac{\Delta V_{bus}}{\Delta T} > 0 \tag{3}$$

where

$$F1 = 0, if, \frac{\Delta V_{bus}}{\Delta T} \le 0 \tag{4}$$

The second feature, $F2$, is derived from the S-transform and is given by,

$$\varsigma 2 = \left| \sum_{m=0}^{N-1} V_{bus}\left[\frac{m+500}{NT}\right] \Phi^{\left(\frac{m}{500}\right)^2} \Gamma^{\frac{mk}{N}} \right| - \left| \sum_{m=0}^{N-1} V_{bus}\left[\frac{m+250}{NT}\right] \Phi^{\left(\frac{m}{250}\right)^2} \Gamma^{\frac{mk}{N}} \right| \tag{5}$$

$$\mathrm{F2} = \rho + 1, \mathrm{if}, \varsigma 2 > 0 \tag{6}$$

$$\mathrm{F2} = 0, \mathrm{if}, \varsigma 2 \le 0 \tag{7}$$

The third feature, $F3$, which is also derived from the S-transform is given by,

$$F3 = \sum_{m=0}^{N-1} V_{bus}\left[\frac{m+500}{NT}\right] \Phi^{\left(\frac{m}{500}\right)^2} \Gamma^{\frac{mk}{N}} \tag{8}$$

where,

V_{bus}: bus voltage

The fourth feature, $F4$, is given by,

$$F4 = \left| \sum_{m=0}^{N-1} P_{bus}\left[\frac{m+500}{NT}\right] \Phi^{\left(\frac{m}{500}\right)^2} \Gamma^{\frac{mk}{N}} \right| - \left| \sum_{m=0}^{N-1} P_{bus}\left[\frac{m+100}{NT}\right] \Phi^{\left(\frac{m}{100}\right)^2} \Gamma^{\frac{mk}{N}} \right| \tag{9}$$

where,

P_{bus}: active power at a selected bus

The input features are usually normalized in the range of 0 to 1 for ANN application. The input features (F1, F2 and F3) and (F1, F2 and F4) are plotted in three dimensions as shown in Figs. 4 and 5, respectively. The plots show that the features can characterize the various events which are grouped into different feature coordinates. The output features of PNN and MLPNN have been determined on the basis of the events which might affect the relay operation during fault, stable swing and unstable swing.

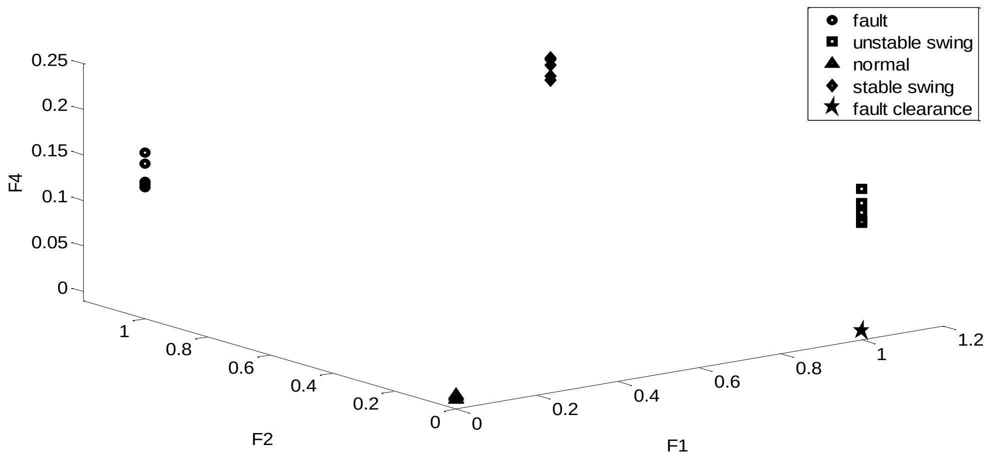

Fig. 4 Plots of input features F1, F2 and F3

As for the output features, the developed PNN classifies fault, stable swing, unstable swing, fault clearance and post fault by representing the events as '1' for fault, '2' for stable swing, '3' for unstable swing, '4' for fault clearance and '5' for post fault. As for MPLNN, the output features consists of [1 0 0 0 0] which denotes a fault, [0 1 0 0 0] as unstable swing, [0 0 1 0 0] as stable swing, [0 0 0 1 0] as fault clearance and [0 0 0 0 1] as post fault. The MLPNN outputs are not in crisp value of 0 or 1, but rather in the range of 0 to 1. Hence, for classification purpose, a decision rule is used so that if the MLPNN output is less than 0.9 or greater than 0.1, it is considered as a misclassified output.

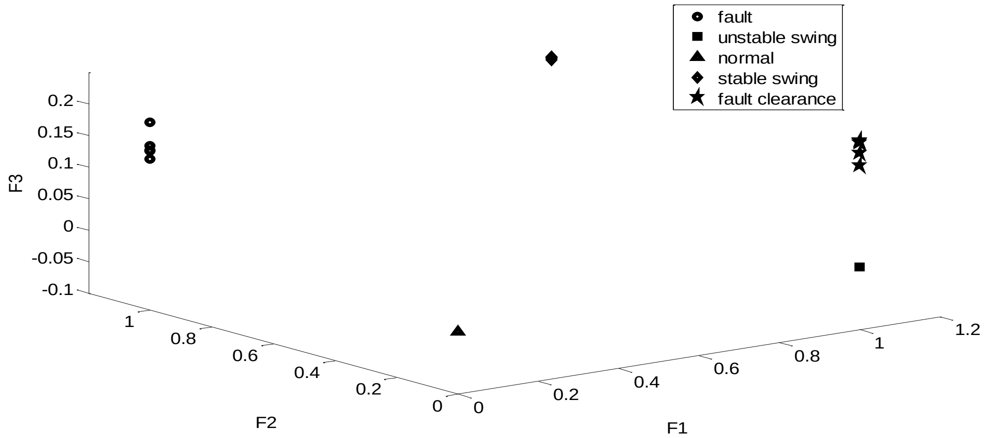

Fig. 5 Plots of input features F1, F2 and F4

III. RESULTS OF ANN FOR CLASSIFYING THREE PHASE FAULT, STABLE AND UNSTABLE SWINGS

Power swing simulations were carried out to generate training data. A fault with duration 350 ms is triggered at different locations of the test systems in order to create different cases of stable and unstable swings. Figs. 6 and 7 show the examples of the time domain simulations illustrating cases of stable and unstable swings

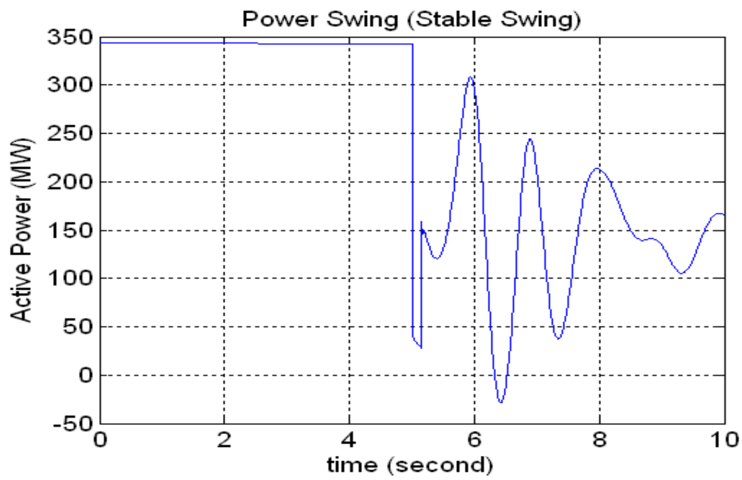

Fig. 6 Time domain simulation illustrating a stable swing

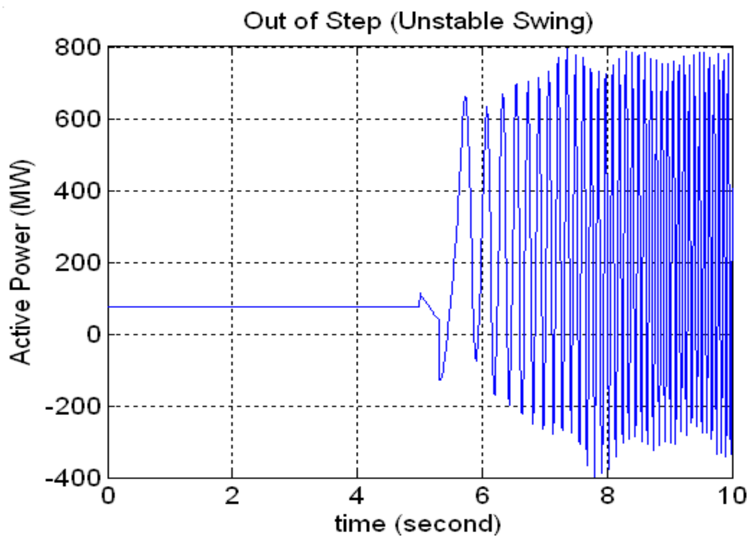

Fig. 7 Time domain simulation illustrating an unstable swing

For the PNN and MLPNN implementation, 60 training data sets consisting of five particular events have been generated, while 75 different data sets have been used for testing purpose. The results obtained from the PNN and MLPNN for detecting and classifying stable swing, unstable swing, fault, fault clearance and post fault for distance relay operation are presented. The fault clearance and post fault have to be considered as the PNN and MLPNN outputs because the features in both situations can be misclassified as a fault or unstable swing if no specific outputs are assigned. The performance of both MLPNN and PNN in predicting the detection time of unstable swing has been evaluated by comparing it with the detection times obtained from simulations.

A. MLPNN Results

The architecture of the MLPNN is such that it has 4 input neurons representing the 4 input features, two hidden layers with 20 neurons and 80 neurons, respectively and 5 output neurons representing stable swing, unstable swing, stable swing, fault clearance and post fault conditions. It uses the hyperbolic tangent transfer function and the back propagation algorithm in the neural network training. The mean squared error which is used as a goal for training the neural network is set at 0.0001. The performance goal was met at 156 epochs with a training time of 10 seconds.

The MLPNN was tested with the 75 sets of testing data and it was found to give an overall accuracy of 93.33% with five misclassifications, among which, three misclassifications are recorded as fault clearance event while the remaining misclassifications are recorded as post fault event. The MLPNN sample testing results are shown in Table 1 in which the bold number in the table denotes the misclassification of events. As shown in Table 1, the MLPNN outputs are not in crisp value of 0 or 1, but rather in the range of 0 to 1. Hence, for classification purpose, a decision rule is used such that if the MLPNN output is less than 0.9 or greater than 0.1, it is considered as a misclassified output.

TABLE I THE MLPNN TESTING RESULTS

Data	**Actual**					**MLPNN**				
SS7	0	0	1	0	0	0.00087	0.00093	0.99825	0.00011	0.0013
SS8	0	0	1	0	0	0.00084	0.00095	0.99836	0.00011	0.0013
SS9	0	0	1	0	0	0.00091	0.00091	0.99804	0.00012	0.0014
SS10	0	0	1	0	0	0.00101	0.00062	0.9927	0.00014	0.0085
PF3	0	0	0	0	1	0.00155	0.00216	0.0005	0.00149	0.9978
PF4	**0**	**0**	**0**	**0**	**1**	**0.99409**	**0.004287**	**0.09097**	**0.81718**	**0.00167**
PF5	0	0	0	0	1	0.00073	0.00177	0.00046	0.00108	0.9994
PF6	0	0	0	0	1	0.0004	0.00001	0.0016	0.00143	0.9945
PF7	0	0	0	0	1	0.00105	0.00053	0.00016	0.00083	0.999
PF14	**0**	**0**	**0**	**0**	**1**	**0.98813**	**0.00262**	**0.00033**	**0.00707**	**0.0004**
PF15	0	0	0	0	1	0.00133	0.00005	0.00203	0.00355	0.9898
FC1	0	0	0	1	0	0.00461	0.00484	0.00568	0.99063	0.0051
FC2	0	0	0	1	0	0.00104	0.00105	0.00007	0.99878	0.0002
FC3	0	0	0	1	0	0.00104	0.00105	0.00007	0.99878	0.0002
FC4	0	0	0	1	0	0.00104	0.00105	0.00007	0.99878	0.0002
FC9	**0**	**0**	**0**	**1**	**0**	**0.03046**	**0.10289**	**0.23232**	**0.07734**	**0.35080**
FC10	**0**	**0**	**0**	**1**	**0**	**0.85367**	**0.10915**	**0.00855**	**0.41258**	**0.25328**
FC11	**0**	**0**	**0**	**1**	**0**	**0.0028375**	**0.12981**	**0.28221**	**0.49346**	**0.030006**
F6	1	0	0	0	0	0.99968	0.00015	0.00011	0.00044	0.0006
F7	1	0	0	0	0	0.99967	0.00019	0.00024	0.00037	0.0008
F8	1	0	0	0	0	0.99867	0.00081	0.00104	0.00021	0.0011
F9	1	0	0	0	0	0.99965	0.00027	0.00034	0.00056	0.0006
						Accuracy		93.33%		

B. PNN Results

The developed PNN classifies fault, stable swing, unstable swing, fault clearance and post fault by representing the events as ‘1’ for fault, ‘2’ for stable swing, ‘3’ for unstable swing, ‘4’ for fault clearance and ‘5’ for post fault. Table 2 shows the sample of PNN testing results in which bold number in the table denotes the misclassification of event. It was found that PNN gives an overall accuracy of 97.33% with two misclassifications recorded as stable and unstable swings. Comparing the testing results of PNN and MLPNN, it can be concluded that the performance of PNN is better than MLPPN in classifying different types of power events during power oscillation phenomena.

TABLE II THE PNN TESTING RESULTS

Data	Actual	PNN	Data	Actual	PNN	Data	Actual	PNN
SS1	2	2	PF11	5	5	F6	1	1
SS2	2	2	PF12	5	5	F7	1	1
SS3	2	2	PF13	5	5	F8	1	1
SS4	2	2	PF14	5	5	F9	1	1
SS5	2	2	PF15	5	5	F10	1	1
SS6	2	2	FC1	4	4	F11	1	1
SS7	2	2	FC2	4	4	F12	1	1
SS8	2	2	FC3	4	4	F13	1	1
SS9	2	2	FC4	4	4	F14	1	1
SS10	2	2	FC5	4	4	F15	1	1
SS11	2	2	FC6	4	4	US1	3	3
SS12	2	2	FC7	4	4	US2	3	3
SS13	2	2	FC8	4	4	US3	3	3
SS14	**2**	**1**	FC9	4	4	US4	3	3
SS15	2	2	FC10	4	4	US5	3	3
PF1	5	5	FC11	4	4	US6	3	3
PF2	5	5	FC12	4	4	US7	3	3
PF3	5	5	FC13	4	4	US8	3	3
PF4	5	5	FC14	4	4	US9	3	3
PF5	5	5	FC15	4	4	US10	3	3
PF6	5	5	F1	1	1	US11	3	3
PF7	5	5	F2	1	1	US12	3	3
PF8	5	5	F3	1	1	US13	3	3
PF9	5	5	F4	1	1	**US14**	**3**	**5**
		Accuracy				97.33%		

C. *Detection Time of Unstable Swing*

The comparison with the frequency deviation technique which has proposed by So et al., (2007) is conducted in order to ascertain the validity and advantages of the propose approaches. In this part, the PN has been chosen instead of MLPNNN due to the high accuracy as mentioned in earlier part of this paper. The frequency deviation is one of the reliable approaches to identify the unstable swing. The results of the techniques have been presented at Table 3. From the result it can be observed that PNN approach is faster as compared to the existing technique. Moreover, the techniques are applicable at transmission network protection with less complexity as compared to frequency deviation which acquires the data from generator to be sent to the transmission.

TABLE III THE PNN TESTING RESULTS RESULT DETECTING TIME OF UNSTABLE SWING

Data	PNN (second)	ω/dω Second)
Data1	0.51	0.61
Data2	0.28	0.45
Data3	0.52	0.61
Data4	0.54	0.61
Data5	0.32	0.45
Data6	0.59	0.61
Data7	0.6	0.61
Data8	0.62	0.61
Data9	0.59	0.61
Data10	0.32	0.5
Data11	0.45	0.53
Data12	0.45	0.5
Data13	0.49	0.53
Data14	0.34	0.53
Data15	0.34	0.53

IV. CONCLUSIONS

To automate the event detection and classification process, results of intelligent classification of three phase fault and voltage collapse using SVM for correct distance relay operation are presented. The test results showed that the SVM performs better than the PNN in detecting and classifying three phase fault and voltage collapse when compared with the actual simulation outputs. Such detection scheme is useful for preventing distance relay from tripping during voltage collapse. Finally, the results of using the proposed combined S-transform and PNN to detect and classify fault, stable swing, unstable swing, fault clearance and post fault are presented. The results showed that the PNN gives a better performance compared to the MLPNN in terms of accuracy. Apart from that, the PNN also proves to be faster on detecting unstable swing event as compared to the frequency detection technique which is proposed by So et. al.

V. ACKNOWLEDGMENT

The authors gratefully acknowledge the Universiti Teknologi MARA for financial support in terms of scholarship and Universiti Kebangsaan Malaysia for financial support on the project.

REFERENCES

[1] Sena, C., Franco, R. & Giusto, A. 2008. Assessment of power swing blocking functions of line protective relays for a near scenario of the Uruguayan system. IEEE/PES Transmission and Distribution Conference and Exposition: Latin America 2008, pp. 1-6.

[2] Zin, A. A. & Karim, S. P. 2007. The Application of Fault Signature Analysis in Tenaga Nasional Berhad Malaysia. IEEE Transaction on Power Delivery 22(4): 2047-2056.

[3] Istardi, D., Abba-Aliyu, S., Bergqvist, A., Rouch, N., Abdalrahman, A. M. & Tuan, L. A. 2009. Understanding Power System Voltage Collapses Using ARISTO: Effects of Protection Interconnected Power Systems. IEEE PowerTech, 2009, pp. 1-7.

[4] Krebs, R., Ziegler, G., Siemen, J. J., Balasiu, F. & Lazar, F. 2009. Avoiding Cascading Protection Tripping in Transmission Systems and Assessment of Quality and Security of the Protection System Power Systems. IEEE PowerTech 2009, pp. 1-7.

[5] M. Jin and T. S. Sidhu, An adptive Load Encroachment Scheme for Distance Protection. Electr. Power Syst. Res. J., vol. 78, pp. 1693-1770, 2008.

[6] Martuscello, L., Krizauskas, E., Holbach, J., & Lu, Y. 2009. Tests of distance relay performance on stable and unstable power swings reported using simulated data of the august 14th 2003 system disturbance. 2009 Power Systems Conference: Advance Metering, Protection, Control, Communication, and Distributed Resources, PSC 2009, pp. 108-128.

[7] Zhang, N., & Kezunovic, M. 2005. A study of synchronized sampling based fault location algorithm performance under power swing and out-of-step conditions. 2005 IEEE Russia Power Tech, PowerTech, pp. 1-7.

[8] Moore, P., & Johns, A. 1996. New method of power swing blocking for digital distance protection. IEE Proceedings: Generation, Transmission and Distribution, 143 (1), 9-26.

[9] Blumschein, J., Yelgin, Y., & Kereit, M. 2008. Proper detection and treatment of power swing to reduce the risk of Blackouts. 3rd International Conference on Deregulation and Restructuring and Power Technologies (DRPT 2008), pp. 2440-2446.

[10] M. Jonsson and J. Daalder, Distance protection and voltage stability. International Conf. on Power Syst. Technology, pp. 971-976, 2000.

[11] Jiao, S., Bo, Z., Liu, W., & Yang, Q. 2001. New Principles to Detect Faults During Power Swing. Seventh IEE International Conference on Developments in Power System Protection, hlm. 515-518.

[12] Su, B., Wang, J., & Xu, Y. 2007. Directional element of distance relay for symmetrical fault during power swing. 8th International Power Engineering Conference, (IPEC 2007), hlm. 482-487.

[13] Xiangning, L., Qing, Z., Wenjun, L., Kecheng, W., & Hanli, W. 2006. Fast Unblocking Scheme for Distance Protection to Identify Symmetrical Fault Occurring During Power Swings. IEEE Power Engineering Society General Meeting, hlm. 1-8.

[14] Zadeh, H., & Li, Z. 2008. Artificial neural network based load blinder for distance protection. IEEE Power and Energy Society 2008 General Meeting: Conversion and Delivery of Electrical Energy in the 21st Century, PES, p. art. no. 4596056.

[15] A. Apostolov, D. Tholomier, and S. Richards, Superimposed components based sub-cycle protection of transmission lines. 2004 IEEE PES Power Syst. Conf. and Exposition, vol. 1, pp. 592-597, 2004

[16] M. Afzali, Esmaeilian, A novel algorithm to identify power swing based on superimposed measurements, 11th International Conference on A. Environment and Electrical Engineering (EEEIC), pp. 1109- 1113, 2012.

[17] B. Mahamedi, Jianguo Zhu, A Novel Approach to Detect Symmetrical Faults Occurring During Power Swings by Using Frequency Components of Instantaneous Three-Phase Active Power, IEEE Transactions Power Delivery, vol. 27, iss. 3, pp. 1368-1376, 2012.

[18] C. Pang and M. Kezunovic, “Fast Distance Relay Scheme for Detecting Symmetrical Fault during Power Swing”, IEEE Transactions on Power Delivery, vol. 25, iss. 4, 2010.

[19] B. Mahamedi, “A Very Fast Unblocking Scheme for Distance Protection to Detect Symmetrical Faults during Power Swing”, Conference Proceedings IPEC, 2010.

[20] Negnevitsky, M. 2005. Artificial Intelligence A Guide to Intelligent Systems. Essex: Addison Wesley.

[21] Mao, K. Z., Tan, K.-C., & Ser, W. 2000. Probabilistic Neural-Network Structure Determination for Pattern Classification. IEEE Transactions on Neural Networks, 11 (4), 1009-1116.

[22] Zaknich, A. 2003. Neural networks for intelligent signal processing. Singapore: World Scientific Publishing Co. Pte Ltd.

[23] R. G. Stockwell, L. Mansinha, and R. P. Lowe, Localization of the complex spectrum: the S transform. IEEE Trans. on Signal Processing, vol. 44, pp. 998-1001, 1996.

Ahmad Farid Bin Abidin received the B.E.E.S degree from University Kebangsaan Malaysia (UKM), Malaysia, in 2000, M.S.E.E. from Universiti Teknologi MARA (UiTM), Malaysia, in 2005 and Ph.D. from University Kebangsaan Malaysia (UKM), Malaysia, in 2011. He is currently a lecturer at the Faculty of Electrical Engineering, UiTM Shah Alam, Malaysia. His research interests are in power system protection and power quality.

Azah Mohamed received her B.Sc. from University of London in 1978 and M.Sc. and Ph.D. from Universiti Malaya in 1988 and 1995, respectively. She is a professor at the Department of Electrical, Electronic and Systems Engineering, Universiti Kebangsaan Malaysia. Her main research interests are in power system security, power quality, artificial intelligence and distributed generation. She is a senior member of IEEE

Hussain Shareef received his B.Sc. with honours from IIT, Bangladesh, M.S. degree from METU, Turkey, and Ph.D. degree from UTM, Malaysia, in 1999, 2002 and 2007, respectively. He is currently an associate professor in the Department of Electrical, Electronics, and Systems Engineering, Universiti Kebangsaan Malaysia. His current research interests are power system deregulation, power quality and power system distribution automation.