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Voltage Stability Prediction on Power System Network via Enhanced Hybrid Particle Swarm Artificial Neural Network

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Abstract – Rapid development of cities with constant increasing load and deregulation in electricity market had forced the transmission lines to operate near their threshold capacity and can easily lead to voltage instability and caused system breakdown. To prevent such catastrophe from happening, accurate readings of voltage stability condition is required so that preventive equipment and operators can execute security procedures to restore system condition to normal. This paper introduced Enhanced Hybrid Particle Swarm Optimization algorithm to estimate the voltage stability condition which utilized Fast Voltage Stability Index (FVSI) to indicate how far or close is the power system network to the collapse point when the reactive load in the system increases because reactive load gives the highest impact to the stability of the system as it varies. Particle Swarm Optimization (PSO) had been combined with the ANN to form the Enhanced Hybrid PSO-ANN (EHPSO-ANN) algorithm that worked accurately as a prediction algorithm. The proposed algorithm reduced serious local minima convergence of ANN but also maintaining the fast convergence speed of PSO. The results show that the hybrid algorithm has greater prediction accuracy than those comparing algorithms. High generalization ability was found in the proposed algorithm.

Keywords: Voltage stability, Fast Voltage Stability Index, artificial neural network, particle swarm optimization, back propagation artificial neural network, prediction, gradient descend

1. Introduction

Power system stability can be divided into angle stability and voltage stability. It can be further divided into transient stability, small signal stability, large disturbance and small disturbance voltage stability [1]. Power system stability refers to the ability of a power system network to retain its functionality when subjected to disturbance. Voltage stability on the other hand refers to the ability of a power system network to maintain its voltage at all the buses without causing the system to fail after subject to disturbance [2]. A sudden increase in load, loss of a heavily loaded transmission line, failure in protective coordination system or insufficient reactive power supply could lead to voltage collapse or in more serious cases can lead to cascading outages and blackouts. Several major voltage collapse cases had been reported in France in 1987, Sweden in 1983, in Japan in 1987 [3], in the USA in 1996 and 2003 [4, 5], Italy in 2003 [5], and England in 2003 [5].

Modern days power system network are being pushed to operate near the threshold due to development and deregulations of electricity market. In order to cater with the increment of severe voltage instability problem, accurate predictions of voltage collapse point and rapid voltage stability analysis with little calculation and processing time become major concern. With the improvement in prediction method and technology, the possibilities of voltage collapse can be figured out and the operator will be able to make adjustment on time to prevent the network goes awry.

Several methods had been used for analysis of static voltage stability. Some methods determine the exact values of voltage collapse such Jacobian method [6], singular value index [7], modal method [8] and voltage sensitivity method [9] while others determine the bifurcation point to predict voltage stability margins [10]. Determination of maximum load enables assessment of proximity to voltage collapse [11], and the use of continuation power flow to determine the weakest bus of the system [12, 13]. Despite all methods described above are used to conduct voltage stability analysis, they were unable to predict or acquire conditions of the stability of the system without intensive calculations. This will consumed a lot of time and instantaneous solution has to be obtained as voltage instability occurs very fast from seconds to just a few minutes. It may be too late to avoid voltage collapse occurrences if the condition of the system is not known instantly. The level of accuracy of these methods also varies from one to another which is an essential factor for voltage collapse avoidance.

The rise of on-line-based voltage stability assessment had brought more possibilities in improving the efficiency and accuracy of voltage stability prediction. The use of various line-based voltage stability indices in on-line

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stability analysis such as Fast Voltage Stability Index (FVSI) [14], Line Stability Index (Lmn) [15], Line Stability Index (Lp) [16], Line Stability Index (NLSI) [17], Voltage Collapse Prediction Index (VCPI) [11] and L-index [18] are common. The use of voltage stability indices are to search for weak buses and give indication of the condition of the buses. L-index formulated by Kessel and Glavitsch [18] had also been used by researchers in power system for the same reason. FVSI was being applied to solve contingency problem of voltage stability in [14, 19] and the results showed good indication on the variation of reactive loadings with good accuracy.

ANN is a common method that had been applied in solving voltage stability problems. ANN is a class of mathematical algorithms that emulate the biological neural networks in the human brain [20, 21]. There are a few models available in the ANN including feedforward network and feedback network, where they had been widely employed in various field in predicting and doing classification. ANN possessed the capabilities of learning and adaptation as well as being able to generalize given information [20, 21]. ANN had been used as earlier as in 1996 in the assessment and enhancement of voltage stability using multiplayer perceptron [22]. However, the method gives several problems as the system cannot be trained too much or too little. The convergence of the load flow solution might sometimes give local minimum after training. As ANN method keeps improving, Radial Basis Function Neural Network had been proposed and claimed to be more superior compared to the previous methods and also capable of determining available transfer capability and stability of voltage in the system [23, 24]. Implementation of feed forward neural network with a stability index is fast and allowing the monitoring of the stability margin in real time after being trained offline [25, 26].

Today, one of the most promising computational intelligence (CI) algorithms came from the Swarm Intelligence (SI). SI consists of a series of algorithms which came from the study on the behaviour and interaction between lower intelligence organisms [27, 28]. There were a lot of SI method proposed and some of the more popular methods that had been applied in the field of electrical studies are the Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC) and Ant Colony Optimization (ACO). Recently, PSO had become popular and had been employed actively in power system and reviews had been carried out to give researchers the basic idea of PSO and its possible applications in various fields of studies [29, 30]. The uprising of PSO had motivated power system researchers to do analysis based on this highly robust algorithm to find global optimum solution in parameter tuning of STATCOM and FACTS device, improving voltage profile through optimal capacitor placement and FACTS devices to reduce losses [31, 32]. PSO had also been discovered to have solved reconfiguration problems in power system noted [32]. PSO has faster convergence rate and is able to search for global optimal solution in most cases with slightly higher computational time compared with GA. Due to each of the CI methods had its own advantages and drawbacks, researchers had started to hybridize various CI together to form a much superior algorithm to solve power system stability problems. [33] had combined GA with ANN in order to solve optimal power flow problems that yield faster computational time with small error in the result.

2. Problem Formulation

By having an accurate prediction on voltage stability condition of the power system network, preemptive decision could be carried out to stop an impending collapse of voltage stability of the network either by operators or automatic devices. The main objective of this study is to minimize the error of the prediction system by reducing the sum of square error between the actual and predicted output information about the stability condition. Therefore, the objective function of the proposed methodology is the sum of square error between the output Fast Voltage Stability Index (FVSI) values and target FVSI values. FVSI is a line stability index proposed by I. Musirin et al. [14] to determine the voltage stability condition of a power system network. He used the concept of power flowing through a single transmission line. From Fig. 1, by assuming that $\delta_1 = 0$ (taking Bus 1 as reference) and $\delta_2 = -\delta$, the current, I can be defined as:

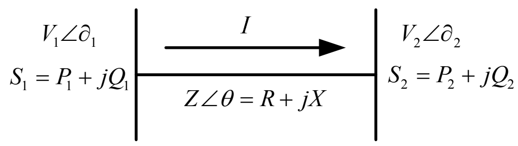

Fig. 1. A typical 2 bus transmission line

$$I = \frac{V_1\angle 0 - V_2\angle -\delta}{R + jX} \tag{1}$$

$$I = \left(\frac{S_2}{V_2}\right)* = \frac{P_2 - jQ_2}{V_2\angle -\delta} \tag{2}$$

$$V_1V_2\angle\delta - V_2^2 = (P_2 - jQ_2)(R + jX) \tag{3}$$

Hence, a quadratic equation of $V2$ can be formed:

$$V_2^2 + V_1V_2\left(\frac{R\sin\delta}{X} - \cos\delta\right) + Q_2\left(\frac{R^2 + X^2}{X}\right) = 0 \tag{4}$$

For real values to exist for V_2, there must be real roots for the equation:

$$V_1^2\left(\frac{R\sin\delta - X\cos\delta}{X}\right)^2 - 4Q_2\left(\frac{R^2 + X^2}{X}\right) \geq 0 \tag{5}$$

Therefore, for the line to be stable and taking the symbol *i* and *j* as sending end and receiving end bus,

$$FVSI_{ij} = \frac{4Z^2 Q_j X}{\left(V_i\right)^2 \left(R\sin\delta - X\cos\delta\right)^2} \le 1 \tag{6}$$

Since $\sin\delta \approx 0$ and $\cos\delta \approx 1$, therefore we can assumed that $R\sin\delta \approx 0$ and $X\cos\delta \approx X$, the *FVSI* can be simplify as:

$$FVSI_{ij} = \frac{4Z^2 Q_j}{\left(V_i\right)^2 X} \tag{7}$$

Then, the FVSI values will be calculated using the load flow program in Matlab programming environment by varying the loadings in the load buses of IEEE 14-bus and 30-bus test system. With all the values of the loadings and their corresponding FVSI values at each transmission lines, sets of data will be generated in order to train the algorithm to perform its prediction duty. With it, sets of data consist of the predicted values and target values will be used to evaluate the sum of square error (SSE) between them, which can be shown in the equation below:

$$SSE = \sum_{i=1}^{m} \left(X_{actual/predicted} - X_{target} \right)^2 \tag{8}$$

where m = 1, 2, 3, 4, 5...m_{max}

Since the aim in this study is to minimize the objective function, so the lower the SSE, the more accurate is the prediction system.

3. Artificial Neural Network

Artificial Neural Network (ANN) is a popular method employed in different field of studies especially mathematics and computer science to solve problems involving estimation, classification, and optimization. ANN emulates the neuron in the brain, transmitting data through its many linkage or pathway. In the process, it will be able to learn, memorize the data sent and be able to interpret the messages. Therefore, an ANN is consists of the input layer with messages or data, the weights as the synapses that connect all the neurons together and an output layer to show the processed information. Through effective training of the weights in ANN, the system will be able to give good solution according to the requirements. There are many types of ANN algorithm such as the back propagation, probabilistic ANN, Kohonen Network and others which differs in terms of training and updating algorithm used.

Feed forward back propagation is one of the most popular types of ANN and had been used in various applications with good accuracy and performance when the correct parameters are selected. Back propagation algorithm trains the ANN weights by returning the error value between the current output and the targeted output of all the input data being used. Using these error values, the weights are being updated through the BP algorithm and again the required outputs will be calculated using the updated weights. The process will be repeated until the accumulated errors or sum of squares of errors had reached a feasible value, the minimum error had been achieved or the ANN had reached certain conditions such as the maximum epoch or minimum threshold. The basic configuration of a BPANN is as shown in the Fig. 2 on next page.

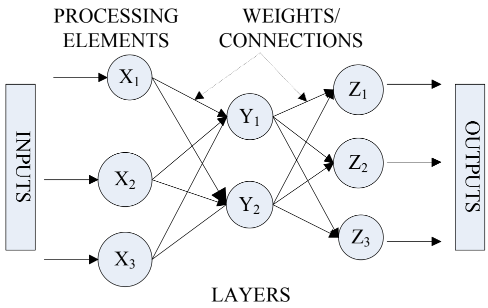

Fig. 2. Configuration of a 3 layers ANN

4. Particle Swarm Optimization

PSO is an optimization technique developed by Kennedy and Eberhart in 1995. The idea came from observing the social behavior of bird flocks flying in synchronism while changing direction and meanwhile, maintaining a safe distance between each of their neighboring birds in an optimal formation. PSO is being classified as a metaheuristic, population-based optimization method that can gives good solution to function-based problems. Compared to other metaheuristic methods like Genetic Algorithm (GA) and Evolution Programming, PSO has its advantages in terms of convergence speed and less susceptible to converge to sub-optimal solution. Besides, PSO has less parameter to alter, rendering easier case by case parameter configuration in order to search for the best configuration and also reduced time required to obtain a solution. In general, PSO technique can be achieved by following the steps below:

(i) Step 1: Initialize the population with a number of particles, N and other parameters

(ii) Step 2: Initialize the position, X and velocity, V of all the particles in the population with random values set within certain range

While the termination criterion is not met or maximum iterations are not reached:

(iii) Step 3: For every particle, the fitness value, F is calculated and compared with the previous best fitness value (pbest). If the current pbest is better (smaller or larger depending on objective function and required solution), replace the previous pbest with current pbest.

(iv) Step 4: Then, choose the best fitness value among all the particles and label it as the global best fitness (gbest).

(v) Step 5: Calculate the particles velocity, V_{new} by using the equation:

$$V_{new} = W_{iter} \times V_{current} + C_1 \times random \times (pbest_{previous} - pbest_{current}) + C2 \times random \times (gbest_{previous} - gbest_{current})$$

(vi) Step 6: Update the particles new position, X_{new} by using the equation:

$$X_{new} = X_{previous} + V_{new}$$

5. EHPSO-ANN

The problem that is needed to solve in this paper is to predict the voltage stability of the transmission system. Therefore, a prediction system must be developed and an indicator must be used so that the voltage stability can be seen clearly and simpler to understand by anyone. A VSI will be used as the indicator, which is the FVSI that is able to give fast and accurate readings of a system's voltage stability on reactive loadings changes. FVSI is chosen due to its sensitivity to reactive load changes and ability to trace voltage stability limit accurately through numerical value. BPANN had always been one of the most effective and efficient algorithm in solving prediction problems, however because of its frequent instability and lacking accuracy that had been mention in the previous section, an improved training algorithm must be applied to the ANN. Due to the fact that PSO is an optimization method, therefore, in order to improve the accuracy of the prediction, an enhanced hybrid PSO-based ANN is being proposed. By replacing the training and updating part of the BPANN with PSO, the new EHPSO-ANN algorithm is formulated in this paper. PSO had been chosen to achieve this objective because PSO has fast convergence rate, has reduced chance to converge into local minimum than BPANN as well as other optimization method like GA, hence improved stability of the overall system and able to obtain high accuracy with low iterations. PSO is responsible for searching the optimal weights for the ANN.

The workings of EHPSO-ANN are divided into following steps as mention in next 2 page and in Fig. 3:

(i) Step 1: Initialize the ANN with the number of layers, numbers of hidden neurons, inputs, outputs and other parameters

(ii) Step 2: Initialize population of PSO, number of particles, randomized the initial position of the particles (in terms of ANN, the weights) and their velocity and other parameters

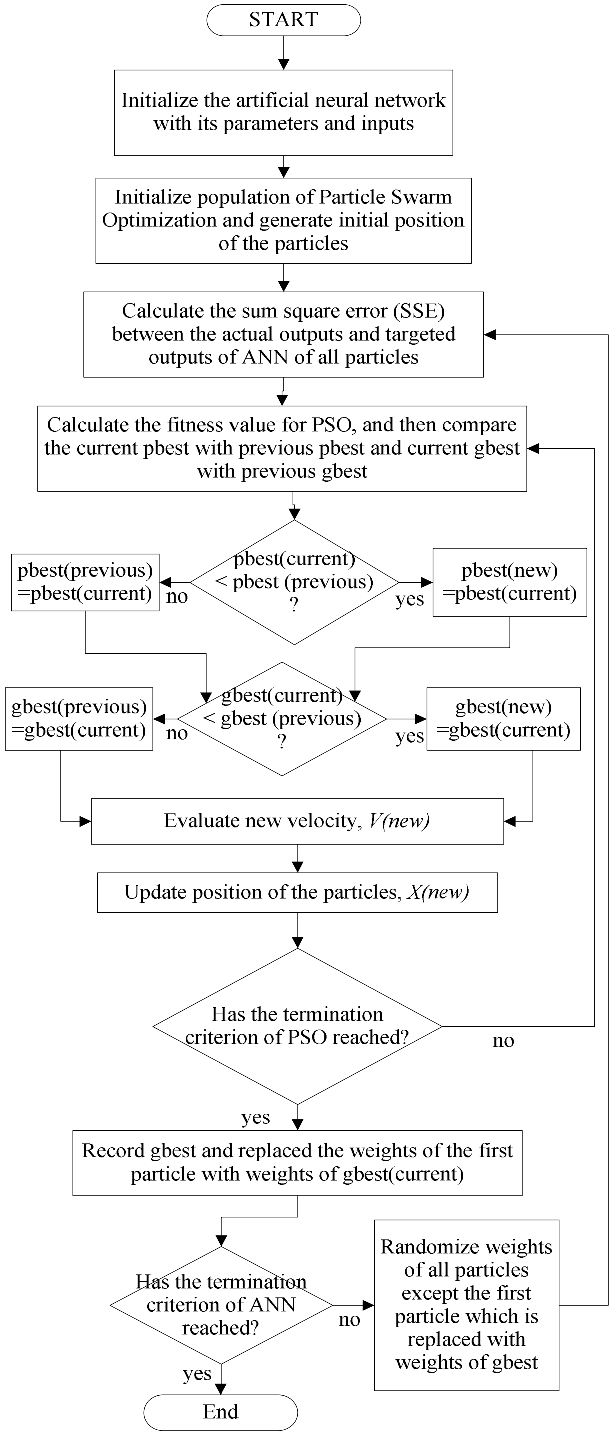

Fig. 3. Flowchart of EHPSO-ANN algorithm

For every particle (Start looping),

(iii) Step 3: Evaluate the ANN by computing their total sum of square error (SSE) between the actual outputs and the targeted outputs.

(iv) Step 4: The SSE from the ANN is passed to the PSO as the fitness value and compared with the previous best fitness value (pbest). If the current pbest is smaller, replace the previous pbest with current pbest.

(v) Step 5: From all the calculated fitness value of the particles, choose the global best, gbest value which contain the minimum fitness value and then store its corresponding weights.

(vi) Step 6: Later, calculate new velocity of the particles and update the new position of the particles.

(vii) Step 7: Repeat steps (iii)-(vi) until the termination criterion had reached or the solution had converged.

(viii) Step 8: Record the gbest of the converged solution and the weights. Then replaced the weights of the first particle in the PSO with the gbest weights of previous iteration.

End Loop.

(ix) Step 9: Repeat Steps (ii)-(viii) by maintaining the gbest's weights from previous epoch on the first particle of PSO while randomizing the weights of other particles until the solution converged or termination criteria had reached.

Several hybrids of PSO with ANN had been proposed by researchers to aid in their respective field of studies. In [34-35], feed forward ANN had been used to hybridize with PSO in weight optimization where the output from the PSO is considered the required solution for the problem. Besides direct implementation of PSO in ANN algorithm which is commonly written as PSO-ANN, [36-38] decided to separate the usage of PSO by first running the ANN program then optimized the output from the ANN using the PSO algorithm. In this paper, feed forward back propagation ANN is being hybridized and modified with the PSO algorithm where the output after the PSO iterations is being back propagated to the ANN again with a certain amount of loops. The enhanced algorithm became a single process. Also, the weights of gbest from the previous loop will become the weights of the first particle of PSO while the rest of the particles will be randomized again. This step is important as to give the algorithm versatility and can avoid PSO from converging into a suboptimal solution by allowing the other particles to search in other spaces within the boundary.

6. Results and Discussion

In order to demonstrate the effectiveness of the proposed EHPSO-ANN algorithm, it will be compared with the BPANN, PSO-ANN [34]-[35] and separate PSO-ANN (SPSO-ANN) [36]-[38] in predicting the voltage stability for IEEE 14-bus and 30-bus test system. Before proceed to the case study, the data has to be provided first to train the system to be able to function properly as a prediction system. To obtain the data, 8 of the load buses in the test system had been varied by randomly increasing their reactive load before passing them to the load flow program. The process will continue until the load flow program diverged and then some of the load buses will be reset to its base loading before continue to collect data. Then the corresponding FVSI value for each line in the test system will be calculated and stored. A total of 300 sets of data had been prepared for the use of the algorithms in 14-bus test system while 800 sets of data were provided by the 30-bus test system. During the training of the system, if the stopping criteria were not fixed, the ANN will continue to operate until it reaches the maximum iteration. In this case, the ANN will become too focused on the training data set and when the testing data set is used, it might give a poor solution due to loss of generalization ability, which this condition was referred to as overtraining. In order to avoid overtraining of the prediction system, validating set had been implemented into both the systems. A 3 layers ANN was used throughout the study. For EHPSO-ANN, PSO-ANN and SPSO-ANN, a total of 100 numbers of iterations was used for 14-bus system and 200 for 30-bus system while BPANN had used 100 for first and second case in 14-bus system while 1000 iteration for 30-bus system, analysis and comparing purposes in the third case of 14-bus system. In 14-bus test system, line connecting bus 13 and bus 14 that is considered the most vulnerable bus is being used as to carry out the FVSI calculations and algorithm tests while for 30-bus test system, line connecting bus 24 and bus 25 is chosen for the same reason stated above.

In the first case, a 5 hidden nodes neural network was used to show the convergence of both the algorithm. With the implementation of velocity clamping in the EHPSO-ANN, it drastically improved the convergence speed of the system and maintained the stability of the system whereby without clamping the particles velocity, the particle might expand its search in a very wide space and might not converge or causes the PSO to fluctuate near the optimal location. Stability of the BPANN algorithm is always an issue and therefore it gave a huge fluctuation and has higher chance of converging into suboptimal solution or in some rare cases, diverged into a bad solution. Therefore, EHPSO-ANN gave a better convergence curve without oscillating intensively near the optimal solution and the convergence speed in unmatched by BPANN. As for the common PSO-ANN, it retains the fast convergence speed of PSO but still oscillate for some time until settled down at its optimal point. However, the SPSO-ANN have the same problem as the BPANN in convergence because it is actually the regular BPANN at the training phase and PSO is being used later on. In the first epoch, the total SSE of both BPANN and SPSO-ANN is high on training phase that is 3.454 and at validating phase, it projects its SSE on 0.390. But for PSO-ANN and EHPSO-ANN, the training phase yields only 2.5442 and 0.1091 respectively on total SSE. During the validating phase, it gives only total SSE of 0.0512 for EH-PSOANN. Because the validating phase for PSO-ANN is done once after the training process, therefore it has only a single validating SSE which is 0.0404. As the epoch increases, the total SSE of BPANN and SPSO-ANN reduces and then oscillates near its suboptimal solution. PSO-ANN also oscillates in the beginning and later on slows down and then completely vanished when the optimal value is reached. However, in EHPSO-ANN, the system barely oscillates and quickly converged into its best solution. In both BPANN and SPSO-ANN, the minimum SSE found are 0.02793 in training phase and 0.007071 in validating phase. For PSO-ANN and EHPSO-ANN, the lowest SSE recorded is 0.0657 and 0.001476 respectively in training phase while for validating phase, their values were recorded as 0.04042 for PSO-ANN and 0.0042 for EH-PSOANN..

The same condition happened in the IEEE 30-bus test system as well. In the training phase of BPANN and SPSO-ANN, the SSE converged with some oscillation but better than in 14-bus system into 0.0282. However, the validating solution shows minimum SSE of 0.2083 and the last epoch at SSE of 0.6441. This shows that both the algorithms converged into a suboptimal solution which is the weakness of the ANN method, and in some paper, if the author did not apply validating phase in his work, he will get even worse solution in the testing phase and lead to poor prediction. For PSO-ANN, the training solution although converged into large SEE value compared to the others, but its validating phase actually converged into a better solution that the 2 methods mentioned before at SSE of 0.1643. The reason is because PSO is capable of fast convergence and will converged into good solution compared with BPANN. As for the proposed method, it was able to converge into good training solution as well as validating phase SSE also gave the best results out of all which is at 0.0137. Table 1, Table 2, Fig. 4, Fig. 5, Fig. 6 and Fig. 7 below show the detailed result mentioned above.

Next, the accuracy of the proposed algorithm is tested by

Table 1. Comparison of Convergence Speed (14 bus)

Conditions	BPANN (SSE)	PSO-ANN (SSE)	SPSO-ANN (SSE)	EH-PSO ANN (SSE)
Training (1st)	3.4540	2.5442	3.4540	0.1091
Validate (1st)	0.3900	-	0.3900	0.0512
Training (last)	0.0279	0.0657	0.0279	0.0015
Validate (last)	0.0071	0.0404	0.0071	0.0042

Table 2. Comparison of Convergence Speed (30 bus)

Conditions	BPANN (SSE)	PSO-ANN (SSE)	SPSO-ANN (SSE)	EH-PSO ANN (SSE)
Training (1st)	2.3946	5.7429	2.3946	0.2778
Validate (1st)	1.2479	-	1.2479	0.1019
Training (last)	0,0282	0.3808	0.0282	0.0166
Validate (last)	0.6441	0.1643	0.6441	0.0137

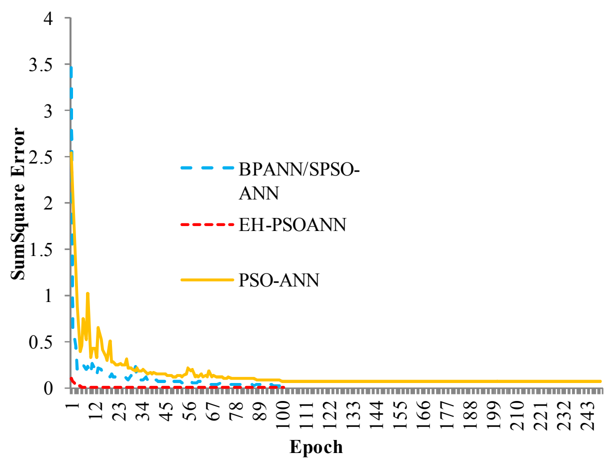

Fig. 4. Convergence curve of training phase (14-bus)

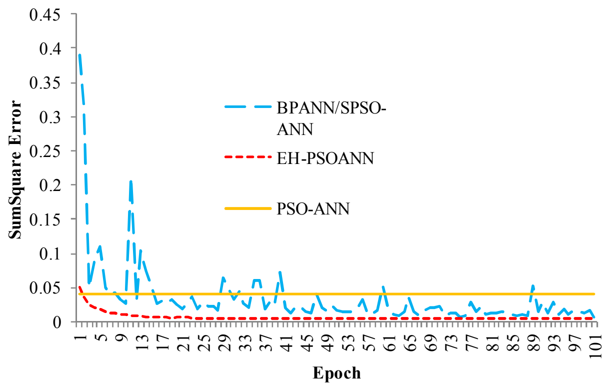

Fig. 5. Convergence curve of validating phase (14-bus)

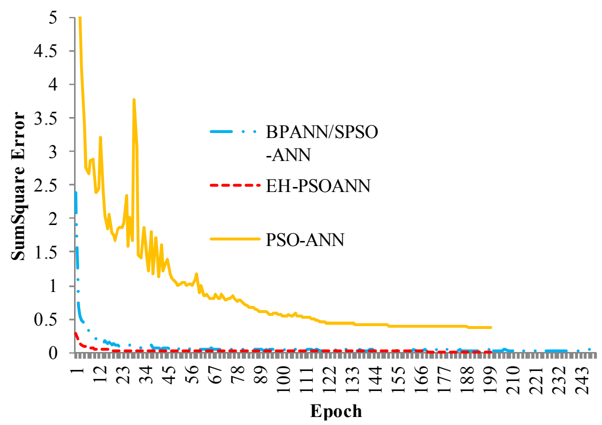

Fig. 6. Convergence curve of training phase (30-bus)

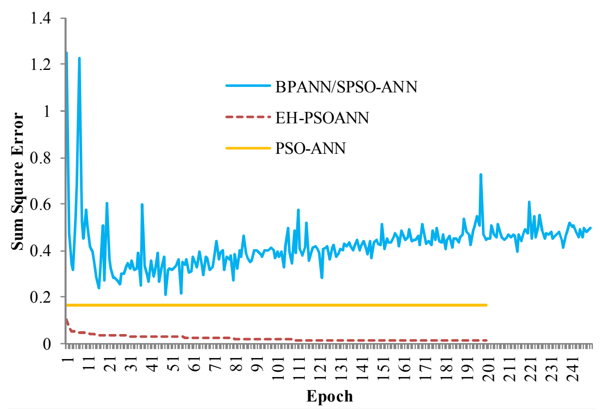

Fig. 7. Convergence curve of validating phase (30-bus)

comparing the SSE of its testing data with the other algorithms and the results can be shown in Table 3, Table 4, Fig. 8 and Fig. 9. The accuracy found in term of SSE in EHPSO-ANN is 0.00409 while BPANN, SPSO-ANN and PSO-ANN only have 0.0222, 0.0131 and 0.037 respectively tested with 14-bus test system. In 30-bus test system, EH-PSOANN also scored the lowest SSE of all other at 0.0107 while BPANN, SPSO-ANN and PSO-ANN registered 0.023, 0.0177 and 0.1643 respectively. While 14-bus test system was used, the total error for EHPSO-ANN is 0.3859 while it is 0.7831 for BPANN, 0.5374 for SPSO-ANN and 1.0376 for PSO-ANN. When these algorithms were tested in 30-bus system, the recorded sum of error were 0.7033 for the proposed algorithm while for the other methods used, the total error increases to 1.5882 for SPSO-ANN, 1.9692 for BPANN and the highest 4.2204 for PSO-ANN. This shows that EHPSO-ANN have the upper hand in the prediction of the voltage stability and this values are very important as the better is the predicted results, the performance of the system and the quality of the

Table 3. Accuracy of both algorithms (14 bus)

Errors	BPANN	PSO-ANN	SPSO-ANN	EH-PSOANN
SSE	0.0222	0.037	0.0131	0.0041
Sum of Errors	0.7831	1.0376	0.5374	0.3859

Table 4. Accuracy of both algorithms (30 bus)

Errors	BPANN	PSO-ANN	SPSO-ANN	EH-PSOANN
SSE	0.0230	0.1643	0.0177	0.0107
Sum of Errors	1.6969	3.6375	1.4382	0.8064

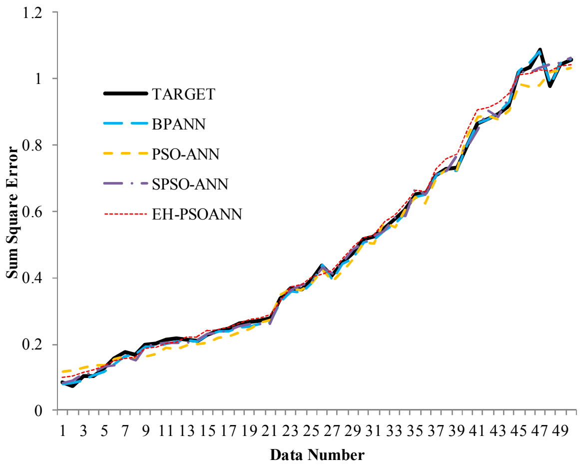

Fig. 8. Graph of testing phase (14-bus)

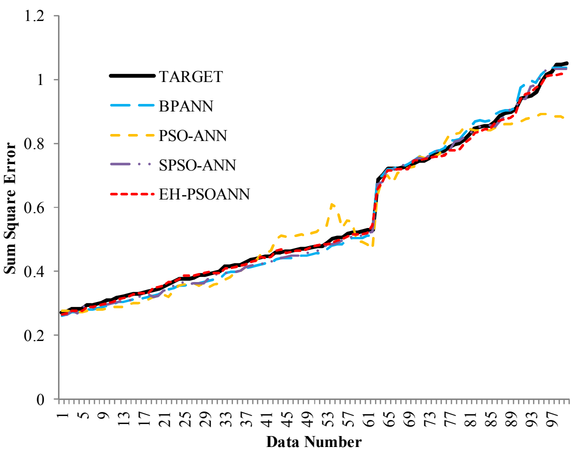

Fig. 9. Graph of testing phase (30-bus)

Table 5. Table of test data (SSE)

TARGET	BPANN	PSO-ANN	SPSO-ANN	EHPSO-ANN
0.0839	0.0793	0.1175	0.0833	0.1000
0.0714	0.0813	0.1191	0.0913	0.1039
0.1017	0.0911	0.1290	0.1094	0.1134
0.1049	0.1052	0.1358	0.1136	0.1212
0.1278	0.1183	0.1368	0.1333	0.1351
0.1547	0.1405	0.1548	0.1367	0.1491
0.1750	0.1636	0.1622	0.1617	0.1583
0.1696	0.1684	0.1556	0.1524	0.1608
0.2000	0.1913	0.1640	0.1932	0.1853
0.2009	0.1924	0.1715	0.1991	0.1904
0.2118	0.1990	0.1884	0.2042	0.2010
0.2154	0.2059	0.1835	0.2023	0.2072
0.2115	0.2096	0.1959	0.2034	0.2200
0.2103	0.2093	0.1989	0.2121	0.2221
0.2282	0.2270	0.2053	0.2309	0.2403
0.2411	0.2369	0.2177	0.2331	0.2450
0.2477	0.2372	0.2237	0.2401	0.2504
0.2611	0.2474	0.2347	0.2512	0.2630
0.2661	0.2528	0.2436	0.2588	0.2730
0.2705	0.2594	0.2635	0.2603	0.2777
0.2767	0.2642	0.2705	0.2621	0.2891
0.3372	0.3252	0.3459	0.3316	0.3310
0.3697	0.3574	0.3657	0.3626	0.3728
0.3641	0.3554	0.3635	0.3786	0.3802
0.3934	0.3812	0.3827	0.3845	0.4009
0.4381	0.4374	0.4225	0.4313	0.4093
0.4058	0.3942	0.3903	0.4108	0.4214
0.4492	0.4424	0.4207	0.4456	0.4583
0.4760	0.4592	0.4547	0.4821	0.4925
0.5142	0.5055	0.5049	0.5047	0.5185
0.5226	0.5148	0.5011	0.5262	0.5264
0.5490	0.5401	0.5655	0.5411	0.5689
0.5778	0.5633	0.5519	0.5810	0.5862
0.6046	0.5939	0.6039	0.5846	0.6206
0.6509	0.6422	0.6411	0.6679	0.6627
0.6557	0.6490	0.6240	0.6518	0.6606
0.7101	0.7108	0.7048	0.7151	0.7280
0.7263	0.7232	0.7268	0.7219	0.7583
0.7314	0.7241	0.7236	0.7670	0.7719
0.8006	0.7988	0.8256	0.7912	0.8462
0.8630	0.8647	0.8838	0.8486	0.9050
0.8807	0.8766	0.8872	0.9020	0.9151
0.8949	0.8959	0.8783	0.8831	0.9267
0.9154	0.9298	0.9027	0.9441	0.9551
1.0198	1.0266	0.9819	1.0216	1.0107
1.0343	1.0460	0.9771	1.0160	1.0166
1.0873	1.0799	0.9793	1.0316	1.0275
0.9760	0.9820	1.0215	1.0420	1.0222
1.0434	1.0480	1.0254	1.0493	1.0364
1.0566	1.0606	1.0317	1.0631	1.0431

electrical supply will improved. Without any modification on the regular PSO-ANN, the algorithm seems to not be able to converge into a better solution because of its advantage, which is the convergence speed. BPANN is slow to converge and could get into a better solution than unmodified hybrid PSO with the help of validating phase but there were also limitation in what it can do. SPSO-ANN gave a solution somewhere in between BPANN and EH-PSOANN. Table 5 is on page 883 and Table 6 is directly on page 884 show the overall test data that had been collected from the algorithm.

Table 6. Table of test data (SSE)

TARGET	BPANN	PSO-ANN	SPSO-ANN	EHPSO-ANN
0.2736	0.2635	0.2760	0.2665	0.2666
0.2755	0.2654	0.2764	0.2672	0.2686
0.2832	0.2724	0.2744	0.2762	0.2772
0.2835	0.2727	0.2743	0.2715	0.2773
0.2846	0.2737	0.2743	0.2923	0.2788
0.2938	0.2822	0.2771	0.2853	0.29
0.2951	0.2833	0.2770	0.2856	0.2901
0.2976	0.2855	0.2808	0.2913	0.2919
0.3028	0.2904	0.2819	0.2966	0.2977
0.3090	0.2939	0.2869	0.2990	0.3002
0.3106	0.298	0.2890	0.3017	0.305
0.3177	0.3036	0.2880	0.3052	0.3114
0.3211	0.306	0.2908	0.3080	0.3171
0.3246	0.3085	0.2972	0.3093	0.3223
0.3290	0.3122	0.3006	0.3116	0.3271
0.3323	0.3156	0.3019	0.3189	0.3319
0.3340	0.3171	0.3047	0.3263	0.3324
0.3386	0.3217	0.3145	0.3281	0.333
0.3408	0.3238	0.3196	0.3211	0.3477
0.3470	0.3296	0.3245	0.3246	0.3505
0.3525	0.3353	0.3273	0.3420	0.3574
0.3623	0.3440	0.3214	0.3445	0.3657
0.3682	0.3495	0.3403	0.3559	0.3657
0.3758	0.3557	0.3551	0.3602	0.3769
0.3769	0.3567	0.3598	0.3672	0.3862
0.3783	0.3581	0.3617	0.3617	0.3873
0.3799	0.3595	0.3641	0.3621	0.389
0.3874	0.3631	0.3554	0.3648	0.3918
0.3883	0.3682	0.3625	0.3654	0.3953
0.3928	0.3728	0.3531	0.3783	0.3982
0.3978	0.3772	0.3605	0.3902	0.3936
0.4010	0.3805	0.364	0.3925	0.3952
0.4166	0.3962	0.3774	0.3942	0.4103
0.4176	0.397	0.3826	0.3978	0.4109
0.4205	0.4003	0.3978	0.3990	0.4129
0.4214	0.4036	0.4045	0.4011	0.4199
0.4299	0.4101	0.4148	0.4153	0.4214
0.4346	0.4139	0.4228	0.4189	0.431
0.4400	0.4183	0.4335	0.4207	0.4346
0.4441	0.4216	0.4525	0.4239	0.4457
0.4467	0.4245	0.4578	0.4286	0.4422
0.4482	0.4256	0.4648	0.4315	0.4443
0.4593	0.4379	0.5004	0.4404	0.4659
0.4614	0.4401	0.5106	0.4421	0.4678
0.4617	0.4406	0.5095	0.4468	0.4586
0.4652	0.4436	0.5102	0.4493	0.4614
0.4662	0.4444	0.5107	0.4495	0.4651
0.4717	0.4488	0.5146	0.4502	0.4665
0.4730	0.4505	0.51	0.4588	0.4682
0.4762	0.4541	0.5199	0.4635	0.4782
0.4787	0.4565	0.5229	0.4653	0.4822
0.4796	0.4582	0.5385	0.4666	0.4849
0.4921	0.4704	0.5438	0.4843	0.4861
0.5028	0.4805	0.6093	0.4858	0.4905
0.5065	0.4855	0.5986	0.4889	0.4956
0.5072	0.4865	0.5345	0.4973	0.5014
0.5170	0.4998	0.558	0.5037	0.5104
0.5229	0.504	0.5571	0.5066	0.5148
0.5237	0.5047	0.4922	0.5113	0.5157
0.5246	0.5056	0.4935	0.5125	0.5181
0.5299	0.5123	0.4838	0.5197	0.5196
0.5301	0.5124	0.4702	0.5246	0.5433
0.6873	0.6883	0.6396	0.6736	0.6575
0.7031	0.7000	0.6922	0.6823	0.6827
0.7202	0.7209	0.7005	0.7184	0.7153
0.7207	0.7218	0.6781	0.7193	0.7157
0.7227	0.7281	0.7093	0.7245	0.7216
0.7245	0.7297	0.7124	0.7310	0.7218
0.7315	0.7365	0.7255	0.7396	0.7216
0.7384	0.7456	0.7291	0.7465	0.7459
0.7461	0.76	0.7575	0.7538	0.7491
0.7467	0.7616	0.7557	0.7503	0.7513
0.7549	0.7682	0.7473	0.7622	0.7551
0.7699	0.7764	0.7602	0.7721	0.7579
0.7735	0.7789	0.7654	0.7815	0.7609
0.7760	0.7864	0.8008	0.7644	0.7637
0.7887	0.8083	0.828	0.7791	0.778
0.7958	0.8106	0.8311	0.8066	0.7805
0.7995	0.8139	0.8352	0.8093	0.7823
0.8108	0.8339	0.8512	0.8217	0.8003
0.8258	0.8492	0.8465	0.8347	0.8157
0.8470	0.8693	0.8394	0.8396	0.8315
0.8499	0.8718	0.841	0.8533	0.8356
0.8535	0.8703	0.8421	0.8561	0.8437
0.8546	0.8727	0.8412	0.8579	0.847
0.8665	0.8931	0.8494	0.8511	0.8654
0.8874	0.9011	0.8550	0.8713	0.8743
0.8933	0.9024	0.8608	0.8882	0.8779
0.8975	0.9056	0.8596	0.9091	0.8815
0.9086	0.9133	0.8634	0.9135	0.8922
0.9413	0.9731	0.8693	0.9398	0.9381
0.9444	0.985	0.8778	0.9402	0.9557
0.9475	0.9962	0.8815	0.9771	0.9604
0.9622	0.9881	0.8842	0.9815	0.9725
0.9934	1.0119	0.8907	1.0092	0.9805
1.0136	1.0299	0.892	1.0299	1.0089
1.0230	1.0357	0.8881	1.0318	1.0125
1.0466	1.0362	0.8851	1.0326	1.0144
1.0487	1.0364	0.885	1.0328	1.0161
1.0497	1.0375	0.8754	1.0334	1.0163

As in the third case, the effect of the number of hidden nodes used is being analyzed. The tests were carried out by varying the hidden nodes to 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15 and 20 hidden nodes in each test respectively. To further improve the accuracy of BPANN and SPSO-ANN, 1000 iteration had been use to test if the algorithm would do better than EHPSO-ANN whereas the number of iteration for EHPSO-ANN was maintained at 100 but no apparent improvement was found. It was found that in EHPSO-ANN, the number of hidden nodes increased do improved the accuracy of the prediction and the best accuracy occurred at 5 hidden nodes for both test systems used. After that, the accuracy started to oscillate up and down as the number of hidden nodes increases. Therefore, 5 hidden nodes with sum square error of 0.0041 in 14-bus system and 0.0107 in 30-bus system were chosen as a reference to carry out all the other analysis. But for BPANN and SPSO-ANN, the accuracy of the prediction shows constant fluctuation and with higher SSE in most of the different numbers of hidden nodes used. Even with the best solution

Table 7. Number of hidden nodes Versus Accuracy (14-bus)

No. of Hidden Nodes	BPANN (SSE)	PSO-ANN (SSE)	SPSO-ANN (SSE)	EHPSO-ANN (SSE)
1	0.0722	0.1073	0.0683	0.0296
2	0.0072	0.0727	0.0081	0.0070
3	0.0067	0.0415	0.0064	0.0053
4	0.0079	0.0399	0.0051	0.0047
5	0.0072	0.0370	0.0058	0.0041
6	0.0057	0.0437	0.0053	0.0050
7	0.0087	0.0389	0.0051	0.0060
8	0.0065	0.0412	0.0061	0.0063
9	0.0071	0.0378	0.0055	0.0052
10	0.0080	0.0381	0.0053	0.0048
15	0.0054	0.0405	0.0052	0.0042
20	0.0060	0.0383	0.0056	0.0060

Table 8. Number of hidden nodes Versus Accuracy (30-bus)

No. of Hidden Nodes	BPANN (SSE)	PSO-ANN (SSE)	SPSO-ANN (SSE)	EHPSO-ANN (SSE)
1	0.1147	0.4163	0.0735	0.0723
2	0.0271	0.1858	0.0203	0.0157
3	0.0266	0.1835	0.0194	0.0114
4	0.0286	0.1731	0.0185	0.0118
5	0.0230	0.1643	0.0177	0.0107
6	0.0254	0.1677	0.0193	0.0112
7	0.0288	0.1662	0.0188	0.0125
8	0.0307	0.1736	0.0192	0.0122
9	0.0296	0.1733	0.0201	0.0114
10	0.0245	0.1808	0.0179	0.0111
15	0.0239	0.1724	0.0181	0.0109
20	0.0242	0.1688	0.0180	0.0116

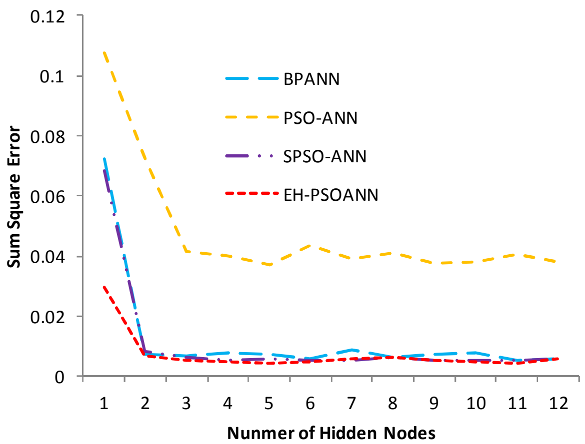

Fig. 10. Graph of SSE versus Number of Hidden Nodes (14-bus)

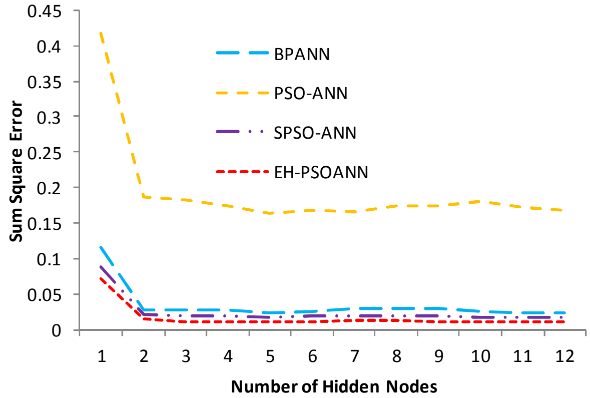

Fig. 11. Graph of SSE versus Number of Hidden Nodes (30-bus)

found by having the optimal number of hidden nodes, other algorithms failed to overpower the solution made by the proposed algorithm even in low number of hidden nodes and high iteration count. Table 7, Table 8 and Fig. 10 and Fig. 11 is provide a clearer view of the results in graphical form.

5. Conclusion

In conclusion, voltage stability of the transmission system is still a very important criterion if reliable and quality power supple is demanded. To avoid voltage collapse that can not only cause trouble to the people but also loss of money due to force halting of machines in factories that might suffer damages, accurate prediction of voltage stability condition is required. By employing PSO algorithms fast convergence and local minimum avoidance ability, the proposed EHPSO-ANN algorithm is able to achieve the objective fast and more than 4 times or 30 percent more accurate than BPANN and 3 times more accurate than SPSO-ANN in the same iteration and 1000 iterations count for BPANN respectively in 14-bus test system. The difference can also be seen when 30-bus test system was used shows the ability of the proposed algorithm is able to work well even in higher bus systems. Unmodified PSO-ANN could not produce feasible result in this paper shows the ability of EH-PSOANN in predicting the voltage stability of the power systems accurately.

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References

[1] P. Kundur, *Power system stability and control*. Tata McGraw- Hill Education, 1994.

[2] M. Randhawa, B. Sapkota, V. Vittal, S. Kolluri, and S. Mandal, "Voltage stability assessment of a large power system," in *Power and Energy Society General Meeting- Conversion and Delivery of Electrical Energy in the 21st Century, 2008* IEEE, pp. 1-7, IEEE, 2008.

[3] C. W. Taylor, "Improving grid behaviour," *Spectrum, IEEE*, vol. 36, no. 6, pp. 40-45, 1999.

[4] M. Klaric, I. Kuzle, and S. Tesnjak, "Undervoltage load shedding using global voltage collapse index," *in Power Systems Conference and Exposition, 2004. IEEE PES*, pp. 453-459, IEEE, 2004.

[5] P. Kundur, J. Paserba, V. Ajjarapu, G. Andersson, A. Bose, C. Canizares, N. Hatziargyriou, D. Hill, A. Stankovic, C. Taylor, et al., "Definition and classification of power system stability IEEE/CIGRE joint task force on stability terms and definitions," *Power Systems, IEEE Transactions on*, vol. 19, no. 3, pp. 1387-1401, 2004.

[6] V. Venikov, V. Stroev, V. Idelchick, and V. Tarasov, "Estimation of electrical power system steady-state stability in load low calculations," *Power Apparatus and Systems, IEEE Transactions on*, vol. 94, no. 3, pp. 1034-1041, 1975.

[7] P.-A. Lof, T. Smed, G. Andersson, and D. Hill, "Fast calculation of a voltage stability index," *Power Systems, IEEE Transactions on*, vol. 7, no. 1, pp. 54-64, 1992.

[8] B. Gao, G. Morison, and P. Kundur, "Voltage stability evaluation using modal analysis," *Power Systems, IEEE Transactions on*, vol. 7, no. 4, pp. 1529-1542, 1992.

[9] N. Flatabo, R. Ognedal, and T. Carlsen, "Voltage stability condition in a power transmission system calculated by sensitivity methods," *Power Systems, IEEE Transactions on*, vol. 5, no. 4, pp. 1286-1293, 1990.

[10] A. Semlyen, B. Gao, and W. Janischewskyj, "Calculation of the extreme loading condition of a power system for the assessment of voltage stability," *Power Systems, IEEE Transactions on,* vol. 6, no. 1, pp. 307-315, 1991.

[11] V. Balamourougan, T. Sidhu, and M. Sachdev, "A technique for real time detection of voltage collapse in power systems," in *Developments in Power System Protection, 2004. Eighth IEE International Conference on*, vol. 2, pp. 639-642, IET, 2004.

[12] V. Ajjarapu and C. Christy, "The continuation power flow: a tool for steady state voltage stability analysis," *Power Systems, IEEE Transactions on,* vol. 7, no. 1, pp. 416-423, 1992.

[13] C. Muriithi, L. Ngoo, G. Nyakoe, and S. Njoroge, "Voltage stability analysis using a modified continuation load flow and optimal capacitor bank placement," *Journal of Agriculture, Science and Technology*, vol. 13, no. 2, 2012.

[14] I. Musirin and T. Abdul Rahman, "Novel fast voltage stability index (fvsi) for voltage stability analysis in power transmission system," in *Research and Development, 2002. SCOReD 2002. Student Conference on*, pp. 265-268, IEEE, 2002.

[15] M. Moghavvemi and F. Omar, "Technique for contingency monitoring and voltage collapse prediction," *IEE Proceedings-Generation, Transmission and Distribution*, vol. 145, no. 6, pp. 634-640, 1998.

[16] M. Moghavvemi and M. Faruque, "Technique for assessment of voltage stability in ill-conditioned radial distribution network," *Power Engineering Review, IEEE*, vol. 21, no. 1, pp. 58-60, 2001.

[17] A. Yazdanpanah-Goharrizi and R. Asghari, "A novel line stability index (NLSI) for voltage stability assessment of power systems," in *Proceedings of 7th International Conference on Power Systems (WSEAS)*, Beijing, China, pp. 164-167, 2007.

[18] P. Kessel and H. Glavitsch, "Estimating the voltage stability of a power system," *Power Delivery, IEEE Transactions on*, vol. 1, no. 3, pp. 346-354, 1986.

[19] I. Musirin and T. A. Rahman, "On-line voltage stability based contingency ranking using fast voltage stability index (FVSI)," in *Transmission and Distribution Conference and Exhibition 2002: Asia Pacific. IEEE/PES*, vol. 2, pp. 1118-1123, IEEE, 2002.

[20] A. P. Engelbrecht, *Computational intelligence: An introduction second edition*. John Wiley & Sons Ltd, 2007.

[21] R. C. Eberhart and Y. Shi, *Computational intelligence: Concepts to implementations.* Morgan Kaufmann Publishers, 2007.

[22] J. Momoh, L. Dias, and R. Adapa, "Voltage stability assessment and enhancement using artificial neural networks and reactive compensation," *in Intelligent Systems Applications to Power Systems, 1996. Proceedings, ISAP'96., International Conference on*, pp. 410-415, IEEE, 1996.

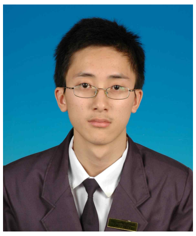
[23] N. Izzri, O. H. Mehdi, A. N. Abdalla, A. S. Jaber, N. A. Shalash, and Y. N. Lafta, "Fast prediction of power transfer stability index based on radial basis function neural network," *International Journal of the Physical Sciences*, Vol. 6(35), pp. 7978-7984, 2011.

[24] K. Chakraborty, A. De, and A. Chakrabarti, "Voltage stability assessment in power network using self organizing feature map and radial basis function," *Computers & Electrical Engineering*, vol. 38, no. 4, pp. 819-826, 2012.

[25] S. Kamalasadan, D. Thukaram, and A. Srivastava, "A new intelligent algorithm for online voltage stability assessment and monitoring," *International Journal of Electrical Power & Energy Systems*, vol. 31, no. 2, pp. 100-110, 2009.

[26] K. Verma and K. Niazi, "Supervised learning approach to online contingency screening and ranking

in power systems," *International Journal of Electrical Power & Energy Systems*, vol. 38, no. 1, pp. 97-104, 2012.
[27] E. Bonabeau, M. Dorigo, and G. Theraulaz, Swarm intelligence: *From natural to artificial systems*, vol. 4. Oxford University Press New York, 1999.
[28] J. F. Kennedy, J. Kennedy, and R. C. Eberhart, *Swarm intelligence*. Morgan Kaufmann, 2001.
[29] A. Banks, J. Vincent, and C. Anyakoha, "A review of particle swarm optimization. Part I: Background and development," *Natural Computing*, vol. 6, no. 4, pp. 467-484, 2007.
[30] A. Banks, J. Vincent, and C. Anyakoha, "A review of particle swarm optimization. Part II: Hybridisation, combinatorial, multicriteria and constrained optimization, and indicative applications," *Natural Computing*, vol. 7, no. 1, pp. 109-124, 2008.
[31] A. Demiroren and M. Guleryuz, "PSO algorithm-based optimal tuning of statcom for voltage control in a wind farm integrated system," in *Electrical and Electronics Engineering (ELECO), 2011 7th International Conference on*, pp. 1-367, IEEE, 2011.
[32] M. Assadian, M. M. Farsangi, and H. Nezamabadi-pour, "GCPSO in cooperation with graph theory to distribution network reconfiguration for energy saving," *Energy Conversion and Management*, vol. 51, no. 3, pp. 418-427, 2010.
[33] W. Nakawiro and I. Erlich, "A combined GA-ANN strategy for solving optimal power flow with voltage security constraint," in *Power and Energy Engineering Conference, 2009. APPEEC 2009. Asia-Pacific*, pp. 1-4, IEEE, 2009.
[34] H. Sayyad, A. K. Manshad, and H. Rostami, "Application of hybrid neural particle swarm optimization algorithm for prediction of MMP," *Fuel*, vol. 116, pp. 625-633, 2014
[35] M. Geethanjali, S. M. R. Slochanal, R. Bhavani, "PSO trained ANN-based differential protection scheme for power transformer," *Neurocomputing, vol. 71*, pp. 904-918, 2008.
[36] M. Khajeh, M. Kaykhaii, and A. Sharafi, "Application of PSO-artificial neural network and response surface methodology for removal of methylene blue using silver nanoparticles from water samples," *Journal of Industrial and Engineering Chemistry*, 2013.
[37] H.-Y. Chen and J.-J. Leou, "Saliency-directed color image interpolation using artificial neural network and particle swarm optimization," *Journal of Visual Communication and Image Representation*, vol. 23, no. 2, pp. 343-358, 2012.
[38] M. Rashidi, M. Ali, N. Freidoonimehr, and F. Nazari, "Parametric analysis and optimization of entropy generation in unsteady MHD flow over a stretching rotating disk using artificial neural network and particle swarm optimization algorithm," *Energy*, 2013.



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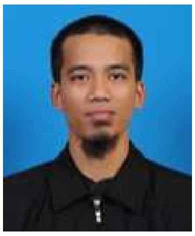

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