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Full Length Research Paper

Fast prediction of power transfer stability index based on radial basis function neural network

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The increase in power demand and limited power sources has caused the system to operate at its maximum capacity. Therefore, the ability to determine voltage stability before voltage collapse has received a great attention due to the complexity of power system. In this paper there is a prediction of Power Transfer Stability Index (PTSI) based on Radial Basis Function Neural Network (RBFNN) for the Iraqi Super Grid network, 400 KV. Learning data has been obtained for various settings of load variables using load flow and conventional PTSI method. The input data was performed by using a 400 samples test with different bus voltage (V_b), Bus active and reactive power (P_b, Q_b), bus load angle (δ_b) and $PTSI_b$. The three RBFNN models have 2, 3 and 4 inputs representing the (V_b, P_b, Q_b and δ_b) respectively, the best hidden layer have thirty six nodes and the output layer has node representing $PTSI_b$ have been used to assess bus security. The proposed method has been tested on a practical system and compared with Back-propagation neural network. In Simulation results show that the proposed method is more suitable for on-line bus voltage stability assessment in term of automatically detection of critical bus when additional real or reactive loads are added or loss of transmission line.

Key words: Voltage stability, radial basis function neural network, voltage collapse.

INTRODUCTION

Recent year's On-line voltage stability assessment (VSA) is considered as an important concern in to power system operation since voltage instability may lead to voltage collapse and total system blackout possibility (Joong et al., 2007; Suthar and Balasubramanian, 2007). The voltage instability can associated with contingencies like unexpected line and generator outages, insufficient local reactive power supply and increased loading of transmission lines. Thus the development of stability assessment has been performed mainly off-line by system planners because the computational burden is too high for online stability assessment. Consequently, in tradition, system planners determine the stability limits of transmission corridors for operators to monitor system. System planners also developed operating guidelines to help operators in the control center to mitigate the problems. Over the last few decades, a number of direct methods for assessment on-line transient stability using non-linear programming technique have been identified and investigated. Zhao et al. (2009) proposes an energy function approach for new models and tools for voltage stability assessment and comes out with voltage stability margin at the system level. Nizam et al. (2006) presented a dynamic description of voltage collapse by characterizing the voltage stability regions in terms of the continuous tap changer model. Haque (2003) used the results of power flow study and the system admittance matrix to find the parameters of the Thevenin's equivalent of the system, looking from various load buses. Lee and Lee (2002) introduced a criterion for static voltage stability enhancement and used accurate models for excitation systems, tap changer and other equipment for analysis of dynamic voltage stability. The voltage stability problem can be considered as a non-issue in distribution systems. However, in modern distribution systems, as they become more complex and large, the issue can be one of the critical problems. There have been some attempts to use ANN for online voltage stability assessment (Kamalasadan

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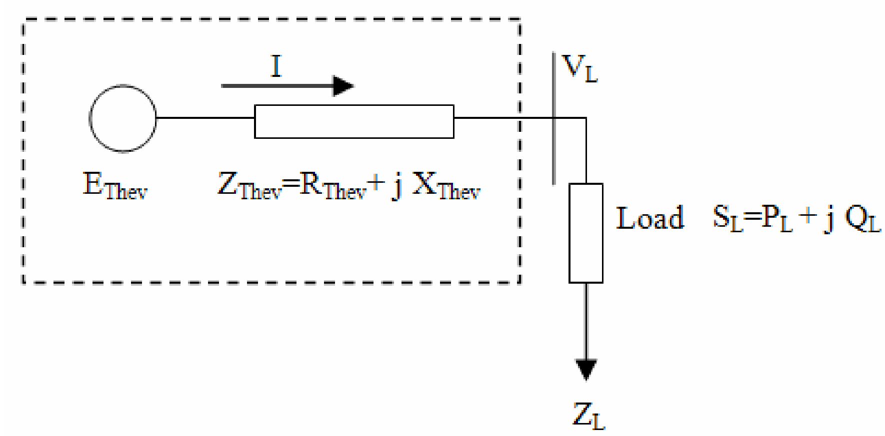

Figure 1. A Simple two-bus Thevenin equivalent system.

et al., 2006) and comes out with voltage stability margin at the system level. In addition, various other methods for voltage stability assessments of power systems have been documented using static and dynamic methods in small radial network was performed by (Hasani and Parniani, 2005). Vu et al. (1994) proposed a simple method of determining the voltage stability margin of an interconnected power system using some local measurements. Taylor (1994) and Kundur (1994) proposed different static methods and dynamic simulation with appropriate models for voltage stability assessments. However, methods based on the dynamic approach are exceptionally time consuming in terms of computer time for the online environment. An especially attractive means for solving the aforementioned problem is found in artificial neural networks (ANNs) (Fischl et al., 1996). Mohammad and Hadi (2008) attempts have been made to set up a direct mapping between the operating states of the system and the VSM index using supervised neural networks (NNs). Celli et al. (2002) proposed ANN predicts L indices (which are simplified measures of maximum loadability of load buses) for all the load buses in a reduced order system.

In this paper, a new intelligent application is developed to improve the voltage stability for Iraq super grid power systems. First, definitions and issues of voltage stability indices are presented. Secondly, the problem has been formulated as by a conventional approach based on the power transfer stability index (PTSI) and the analytical work done including various line outages and for various reactive power control variables and loading conditions to predicting system performance and using these data to training RBFNN. Thirdly, three different RBFNN models have been used with 2, 3 and 4 inputs (which represent Bus data). Finally, the tests were carried out on the eastern part of the high-voltage power system of former Iraqi super grid 400 KV to demonstrate its favorable performance by using MATLAB 10 neural network toolbox. In addition the performance of proposed method compared with Back-propagation neural network including its capabilities and limitations of are discussed.

RELATED WORK

Power transfer stability index

The proposed dynamic voltage collapse indicator named as the Power Transfer Stability Index (PTSI) is derived by considering a simple two-bus Thevenin equivalent system, with a slack bus connected to a load bus by a single branch as shown in Figure 1. Referring to Figure 1, the current drawn by the load is given by,

$$\bar{I} = \frac{\bar{E}_{Thev}}{\bar{Z}_{Thev}+\bar{Z}_L} \tag{1}$$

The load apparent power can be written as,

$$\bar{S}_L = \bar{Z}_L \bar{I}\bar{I}^* = \bar{Z}_L |\bar{I}|^2 \tag{2}$$

Substituting equation (1) into (2) we get,

$$\bar{S}_L = \bar{Z}_L \left|\frac{\bar{E}_{Thev}}{\bar{Z}_{Thev} + \bar{Z}_L}\right|^2 \tag{3}$$

Considering that $\bar{Z}_L = Z_L\angle\alpha$ and $\bar{Z}_{Thev} = Z_{Thev}\angle\beta$ and substituting them into (2), we get,

$$\bar{S}_L = Z_L\angle\alpha \left|\frac{E_{Thev}}{Z_{Thev}\angle\beta + Z_L\angle\alpha}\right|^2 \tag{4}$$

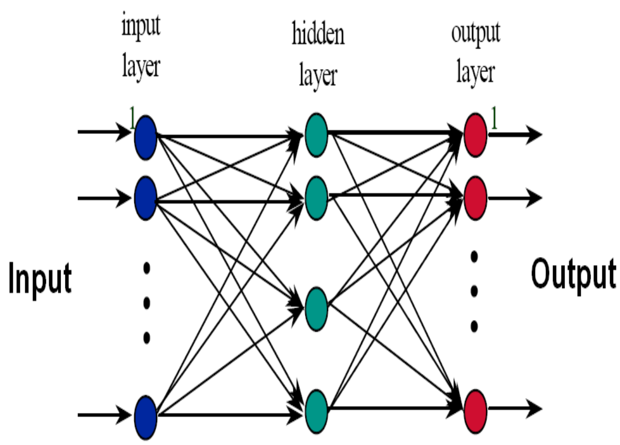

Figure 2. Radial basis function neural networks.

The magnitude of load apparent power SL from (4) can be expressed as,

$$\bar{S}_L = \frac{E_{Thev}^2 Z_L}{|Z_{Thev}\angle\beta + Z_L\angle\alpha|^2} \quad (5)$$

Expanding S_L from (5), we get

$$S_L = \frac{E_{Thev}^2 Z_L}{Z_{Thev}^2 + Z_L^2 + 2Z_{Thev}Z_L \cos(\beta-\alpha)} \quad (6)$$

The maximum load apparent power SL is then determined by considering $\partial S_L/\partial Z_L = 0$. Maximum load apparent power becomes,

$$S_{Lmax} = \frac{E_{Thev}^2}{2Z_{Thev}(1+2\cos(\beta-\alpha))} \quad (7)$$

To assess the load bus distance to voltage collapse, a power margin is defined as $S_{Lmax} - S_L$. The power margin equals to 0 if $Z_L = Z_{Thev}$ and it implies that power cannot be transferred at this point and a voltage collapse is said to occur. In other words, a voltage collapse will occur if the ratio,

$$\frac{S_L}{S_{Lmax}} = 1 \quad (8)$$

Substituting Equations (6) and (7) into (8), the proposed PTSI is obtained and expressed as,

$$PTSI = \frac{2S_L Z_{Thev}(1+\cos(\beta-\alpha))}{E_{Thev}^2} \quad (9)$$

Using equation (9), PTSI is calculated at every bus by using information of the load power, Thevenin voltage and impedance and load impedance phase angles. The value of PTSI will fall between 0 and 1 such that when PTSI value reaches 1, it indicates that a voltage collapse has occurred (Muhammad et al., 2007).

Radial basis function neural network

RBFNN have increasingly attracted interest for engineering applications due to their advantages over traditional multilayer perceptions, namely faster convergence, smaller extrapolation errors, and higher reliability. Over the last few years, more sophisticated types of neurons and activation functions have been introduced in order to solve different sorts of practical problems (Kumar, 2005; Kurban and Beşdok, 2009). In particularly, RBFNN have proved very useful for many systems and applications (Kumar, 2005). RBFNN is defined as a kind of ANN that has radial activation functions on its intermediary layer. RBFNN were robust used in the context of neural networks as linear and nonlinear function estimators and indicated their interpolation capabilities by Broomhead and Lowe (Broomhead and Lowe, 1988). (Hartman et al., 1990; Park and Sandberg, 1993) proved that RBFNN are capable of approximating any function with arbitrary accuracy. The neural network is a mapping between its inputs and outputs based on a number of known sample input-output pairs. In general, the more samples available to train the network, the more accurate the representation of the real mapping will be. These samples are obtained by solving the direct problem (times), in its simplest form, a RBFNN consists of three layers of neurons as shown in Figure 2. The first layer acts as the input layer of the ANN. The second layer is hidden layer as a high-scale dimension, which promotes a linear transformation of input space dimension by computing radial functions in their neurons. Third layer, the output layer, outputs the ANN response, promoting a linear transformation of the intermediary layer high-scale dimension to the low-scale dimension (Pandya, 1995).

MATERIALS AND METHODS

RBFNN Model for PTSI

Several types of ANN structures and training algorithms have been proposed as shown in Figure 3. The basic form of RBFNN architecture involves entirely three different layers. The input layers is made *n*, of source nodes while the second layer is hidden layer of high enough dimension which senses a different purpose from that in a multilayer perception.

The output layer supplies the response of the network to the activation patterns applied to the input layer. The transformation from the input layer to the hidden layer is nonlinear whereas the transformation from the hidden layer to the output layer is linear.

From above analytical methods involve considerable computational effort and hence cannot be used directlyfor online monitoring and initiation of preventive control actions to enhance system voltage stability. The major steps of the RBFNN design and training to determining the voltage instability problem a resummarized by the

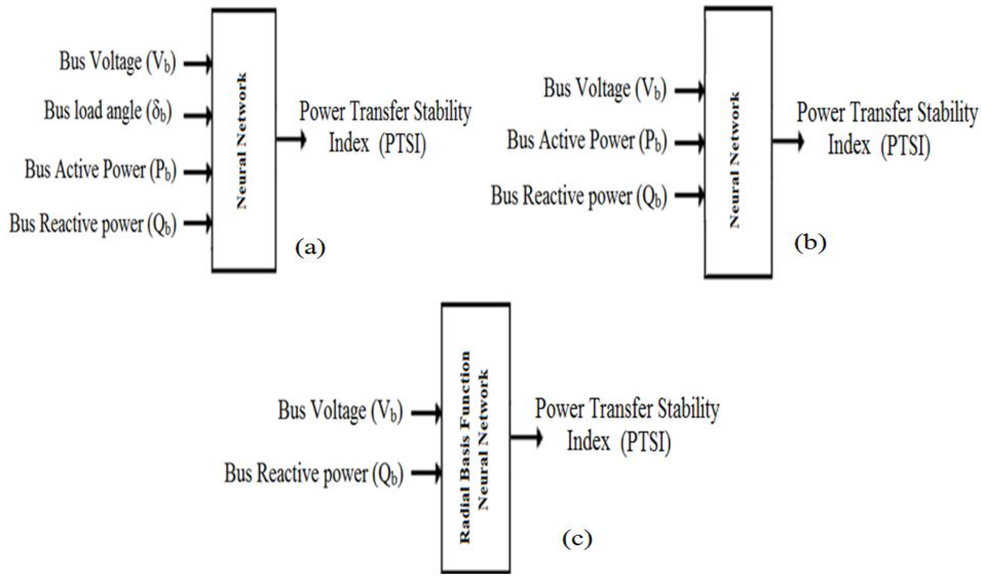

Figure 3. PTSI Predication model based on ANN.

following steps:

(i) A set of realistic system loading patterns are generated by varying the real power and reactive power loadings at various line outages and for various variables loading conditions.
(ii) For each of the loading patterns generated in step (i) the load flow and modal analysis of the reduced Jacobian matrix are done and PTSI was calculated for each bus in the system to identify the most vulnerable few load buses from the voltage stability point of view.
(iii) The RBFNN are designed and trained by deferent's input patterns (V_b, δ_b, P_b, Q_b) for each bus is generated as shown in Figure 3.
(iv) The RBFNN, the target output is PTSI to show distance to voltage collapse for each input pattern is computed by running the contour program.
(v) Training of these RBFNN using the input/output patterns developed in Steps 3 and 4 is carried out.
(vi) Finally, the outputs of three models have been compared to check the sensitivity of bus stability index based on the four input parameter.

Iraqi super grid network

The transmission level in the Iraqi electrical network consists of the 400 KV network (the super grid network) and part of the 132 kV network connected to it. The aim of this work is limited to the study of only the 400 KV network with all its bus-bars and transmission lines. The network under consideration consists of 24 bus bars and 30 transmission lines (the total transmission line 3664.6 Km) and configuration of this network (Omer et al., 2011).

RESULTS AND DISCUSSION

To demonstrate the effectiveness of the proposed technique for online voltage stability monitoring for different types of contingencies including variable load and line outage has been applied to the Iraqi super grid network 24-bus test system. Two different cases used for generating training data (for both the RBFNN, BPNN) active and reactive power set the load buses are varied random load ± 25% base case values; (b) Fix active and reactive powerset the load buses and most critical line outages. Foreach operating condition, bus operating parameters are recorded as the input features. The experiment results were used to train the neural network which have been constructed and trained using 400 data samples from the experimental data and 20 samples were used for generalization test of the trained neural network.

Case 1: Varied random load (dynamic stability)

From Tables 1 and 2, it is clear that Iraqi power system working with limited power sources has caused the system to operate at its maximum capacity. In addition, the maximum error depend on number of inputs for RBFNN, that is the RBFNN can get better result depend of training input data but with long training time. In addition, Both RBFNN and BPNN have superior CPTSI.

From Table 3, it is clear that RBFNN faster than BPNN and nearly not depend on training data. Speed of training PBNN depend on the size of training data that is the time increasing with increasing training data.The average errorsapproximately samefor both RBFNN and BPNN.

Case 2: Contingency (line outages)

Contingency analysis is performed for all line outages and the most critical transmission line in the system has been identified and appropriate algorithms tha is TL6-15 is

Table 1. PTSI prediction based on RBFNN for loaded buses with varied random load.

No.	Bus no.	CPTSI	(4 Inputs)		(3 Inputs)		(2 Inputs)	
			RBFNN output	Error	RBFNN output	Error	RBFNN output	Error
1	3	0.987914	0.96785	0.020064	0.963095	0.024819	0.95834	0.029574
2	6	0.954004	0.939169	0.014835	0.934326	0.019678	0.929483	0.024521
3	7	0.981182	0.973121	0.008061	0.971444	0.009738	0.969766	0.011416
4	8	0.973669	0.957885	0.015784	0.954733	0.018936	0.951581	0.022088
5	9	0.983717	0.964664	0.019053	0.960133	0.023584	0.955602	0.028115
6	11	0.977562	0.966569	0.010993	0.964461	0.013102	0.962352	0.01521
7	12	0.957789	0.946098	0.011691	0.942017	0.015772	0.937936	0.019853
8	13	0.974447	0.959171	0.015276	0.95661	0.017838	0.954048	0.020399
9	14	0.939308	0.928461	0.010847	0.932732	0.006576	0.937003	0.002305
10	16	0.993132	0.995873	-0.00274	0.994685	-0.00155	0.993497	-0.00036
11	19	0.991891	0.992188	-0.0003	0.992592	-0.0007	0.992996	-0.00111
12	20	0.977767	0.976676	0.001091	0.978782	-0.00101	0.980887	-0.00312
13	22	0.950816	0.946258	0.004558	0.951221	-0.0004	0.956183	-0.00537
		Maximum error		0.020064		0.024819		0.029574
		Average ABS error		0.010407		0.011823		0.014111

Table 2. PTSI prediction based on BPNN for loaded buses with varied random load.

No.	Bus no.	CPTSI	(4 Inputs)		(3 Inputs)		(2 Inputs)	
			BPNN output	Error	PBNN output	Error	BPNN output	Error
1	3	0.987914	0.961169	0.026745	0.955465	0.032449	0.975206	0.012708
2	6	0.954004	0.932457	0.021547	0.926695	0.027309	0.946307	0.007697
3	7	0.981182	0.969501	0.011681	0.966857	0.014325	0.980517	0.000665
4	8	0.973669	0.952824	0.020845	0.948726	0.024943	0.965165	0.008504
5	9	0.983717	0.958213	0.025504	0.952735	0.030982	0.971995	0.011722
6	11	0.977562	0.962532	0.01503	0.959465	0.018097	0.973915	0.003647
7	12	0.957789	0.940133	0.017656	0.935122	0.022667	0.953288	0.004501
8	13	0.974447	0.954697	0.01975	0.951186	0.023261	0.966461	0.007986
9	14	0.939308	0.930867	0.008441	0.934192	0.005116	0.935517	0.003791
10	16	0.993132	0.992696	0.000436	0.990517	0.002615	1.003442	-0.01031
11	19	0.991891	0.990607	0.001284	0.990017	0.001874	0.999729	-0.007838
12	20	0.977767	0.976824	0.000943	0.977944	-0.000177	0.984099	-0.006332
13	22	0.950816	0.949319	0.001497	0.953314	-0.002498	0.95345	-0.002634
		Maximum error		0.026745		0.032449		0.012708
		Average ABS error		0.013185		0.016673		0.018349

Table 3. Compare the Performance of RBFNN and BPNN.

CPTSI	RBFNN		BPFNN	
	Ave. error	Time (s)	Ave. error	Time (s)
4 Inputs	0.010407	0.152739	0.013185	0.300316
3 Inputs	0.011823	0.162183	0.016673	0.235524
2 Inputs	0.014111	0.159696	0.018349	0.196094

unstable under same load in case 1. From Table 2, it can observed that Bus 6 (PSTI = 0.9997) is most effect bus by this transmission line because this TL cut one supported source for this load bus and on the other hand bus 3 and 16 get better compared with case 1 (PSTI = 0.877914 and 0.954126 respectively). In addition, Bus 9 also is affected

Table 4. PTSI prediction based on RBFNN for TL6-15 with varied random load.

No.	Bus no.	CPTSI	(4 Inputs)		(3 Inputs)		(2 Inputs)	
			RBFNN output	Error	RBFNN output	Error	RBFNN output	Error
1	3	0.877914	0.85215	0.025764	0.85536	0.022554	0.850718	0.027197
2	6	0.999754	0.999685	0.000115	0.999511	0.000273	0.999665	0.000121
3	7	0.983282	0.972811	0.010471	0.974338	0.008944	0.972705	0.010577
4	8	0.981669	0.961308	0.020361	0.964222	0.017447	0.961157	0.020512
5	9	0.991891	0.966532	0.025359	0.970465	0.021426	0.966042	0.02585
6	11	0.989422	0.975334	0.014088	0.977314	0.012108	0.975266	0.014156
7	12	0.986723	0.969764	0.016959	0.972922	0.013801	0.968911	0.017813
8	13	0.975392	0.956212	0.019180	0.958752	0.01664	0.956274	0.019119
9	14	0.941528	0.934457	0.007071	0.932773	0.008755	0.937088	0.004441
10	16	0.954126	0.955793	-0.00167	0.956282	-0.00216	0.955081	-0.00096
11	19	0.996591	0.997347	-0.00076	0.997094	-0.00050	0.997496	-0.00091
12	20	0.976567	0.977656	-0.00109	0.976526	4.07E-05	0.978632	-0.00207
13	22	0.951416	0.95185	-0.00043	0.949327	0.002089	0.954301	-0.00289
		Maximum error		0.025764		0.022554		0.027197
		Average ABS error		0.009749		0.011024		0.011278

Table 5. PTSI prediction based on BPNN for TL6-15 with varied random load.

No.	Bus no.	CPTSI	(4 Inputs)		(3 Inputs)		(2 Inputs)	
			PBNN output	Error	BPNN output	Error	BPNN output	Error
1	3	0.877914	0.847315	0.010599	0.864085	0.011829	0.865955	0.011959
2	6	0.999754	1.000865	-0.00111	1.009706	-0.00995	1.01588	-0.01613
3	7	0.983282	0.973872	0.00941	0.984276	-0.00099	0.988571	-0.00529
4	8	0.981669	0.96231	0.010359	0.974057	0.007612	0.976881	0.004788
5	9	0.991891	0.967201	0.02469	0.980364	0.011527	0.98219	0.009701
6	11	0.989422	0.976436	0.012986	0.987283	0.002139	0.991134	-0.00171
7	12	0.986723	0.970074	0.016649	0.982846	0.003877	0.985474	0.001249
8	13	0.975392	0.957422	0.01797	0.968531	0.006861	0.971703	0.003689
9	14	0.941528	0.938213	0.003315	0.942287	-0.00076	0.949595	-0.00807
10	16	0.954126	0.956227	-0.0021	0.966036	-0.01191	0.971277	-0.01715
11	19	0.996591	0.998693	-0.0021	1.007264	-0.01067	1.013504	-0.01691
12	20	0.976567	0.979806	-0.00324	0.986487	-0.00992	0.993494	-0.01693
13	22	0.951416	0.955446	-0.00403	0.95901	-0.00759	0.96727	-0.01585
		Maximum error		0.010599		0.011829		0.013959
		Average ABS error		0.011351		0.01751		0.019956

because bus 6 start depends on it to support the load demands and bus 20 and 22 is very less affected by this TL.

Form Tables 4 and 5, it is clear that the RBFNN's response same as in case 1 which 4 input RBFNN is slightly superior when compared to the CPTSI and Both RBFNN and BPNN have superior CPTSI.

From Table 6, it is clear that RBFNN faster than BPNN and nearly not depend on training data. Speed of training PBNN depend on the size of training data that is, the time increasing with increasing training data. The average errors approximately same for both RBFNN and BPNN.

Finally, for the analysis of above the results, it is observed that the accuracy of the 4 input-RBFNN method was slightly superior when compared to the CPTSI on account of maximum error both cases but 2 input-RBFNN method was fast for PTSI prediction compared to the CPTSI and 3 input-RBFNN method keep in midpoint in term of accuracy and time.

Conclusion

In this study voltage stability assessment of power systems

Table 6. Compare the performance of RBFNN and BPNN.

CPTSI inputs	RBFNN		BPFNN	
	Ave. error	Time (s)	Ave. error	Time (s)
4	0.009749	0.149839	0.011351	0.297316
3	0.011024	0.159783	0.01751	0.226624
2	0.011278	0.158796	0.019956	0.198794

by using RBFNN has been explored, and this was obvious from the generalization test. The simulation data from PTSI test has been used for training and testing.Using this approach, for a given operating condition, the most critical transmission line of the system has been identified and appropriate algorithms, which directly employ the designed NN architecture, have been suggested to evaluate on-line the previously considered control strategies. The difference of PTSI between prediction by RBFNN and CPTSI test is considered almost negligible; this means that it can solve many problems that have been costly and time consuming.The effectiveness of the proposed approach has been tested on Iraqi super grid power system.

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