

Fast Prediction of Voltage Stability Index Based on Radial Basis Function Neural Network: Iraqi Super Grid Network, 400-kV

Omer H. Mehdi & Noor Izzri

Department of Electrical and Electronic Engineering, Faculty of Engineering
University Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia

Mohammad K. Abd

Department of Electrical and Electronic Eng., University of Technology, Baghdad, Iraq

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Abstract

With the increase in power demand and limited power sources has caused the system to operate at its maximum capacity. Therefore, the ability of determine voltage stability before voltage collapse has received a great attention due to the complexity of power system. In this paper a prediction of voltage stability index (VSI) based on radial basis function neural network (RBFNN) for the Iraqi Super Grid network, 400KV. Learning data has been obtained for various settings of load variables using load flow and conventional FVSI method. The input data was performed by using a 135 samples test with different bus voltage (V_b), Bus active and reactive power (P_b , Q_b), bus load angle (δ_b) and $FVSI_{ij}$. The RBFNN model has four input representing the (V_b , P_b , Q_b and δ_b), sixteen nodes at hidden layer and one output node representing $FVSI_{ij}$ have been used to assess the security on line. The proposed method has been tested in the IEEE 30 and a practical system. In Simulation results show that the proposed method is more suitable for on-line voltage stability assessment in term of automatically detection of critical transmission line when additional real or reactive loads are added.

Keywords: Voltage stability index, Radial basis function neural network, Voltage collapse

1. Introduction

Recent year's voltage stability is considered as an important concern in to power system operation and planning since the heavily loaded systems are mostly operated closer to the reactive power limits of the transmission network (Suthar and Balasubramanian, 2007). The voltage problems are often associated with contingencies like unexpected line and generator outages, insufficient local reactive power supply and increased loading of transmission lines. However, 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 to mitigate the problems.

Over the last few decades, a number of direct methods for assessment on-line transient stability have been identified and investigated. This gives more and higher requirements for new models and tools for voltage stability analysis (Zhao et al., 2009). The voltage instability can occur when a power system is heavily loaded in transmission lines and/or lacks in local reactive power sources (Joong, 2007). Although the voltage stability problem is in its nature a dynamic one, a great deal of the research work has been devoted to the static methods in real-time applications. (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 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 Pamiani, 2005). Some advantages of dynamic simulation of this phenomenon were shown by (Deuse and Stubbe, 1993). (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, 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).

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 Fast voltage Stability Index (FVSI) and FVSI have been obtained for various line outages and for various reactive power control variables and loading conditions and using these results a RBFNN ANN is trained. Finally, the tests were carried out on the eastern part of the high-voltage power system of former Iraqi super grid 400KV to demonstrate its favorable performance by using MATLAB 10 neural network toolbox.

2. Related Work

A) Conversional Fast Voltage Stability Index

Fast voltage stability index (FVSI) is formulated in this study as the measuring instrument in predicting the voltage stability condition in the system. The proposed index made used the same concept as the existing ones (Moghavemmi and Omar, 1998 and Mohamed et al., 1989) in which discriminate is set to be greater or equal than/to zero to achieve stability. If the discriminate is small than zero, the roots for the voltage or could cause instability in the system. The mathematical formulation is very simple that could speed up the computation. The condition of voltage stability in a power system can be characterized by the use of voltage stability index referred to line. Generally, it started with the current equation to form the power or voltage quadratic equations. The criterion employed in this paper was to set the discriminate of the roots of voltage or power quadratic equation to be greater than zero. When the discriminate is less than zero, it causes the roots of the quadratic equations to be imaginary which in turn causing the voltage instability that may cause voltage collapse in the system. The line index that is evaluated close to 1.00 will indicate the limit of voltage instability.

Fig.3. illustrates a 2-bus power system model where the proposed FVSI is derived from the symbols are explained as follows:

V_i, V_j = Voltage on sending and receiving buses

P_i, Q_i = Active and reactive power on the sending bus

P_j, Q_j = Active and reactive power on the receiving bus

S_i, S_j = Apparent power on the sending and receiving buses

$\delta_{ij} = \delta_i - \delta_j$

= Angle difference between sending and receiving buses

The line impedance is noted as $Z_{ij} = R_{ij} + jX_{ij}$ with the current that flows in the line IS given by

$$I = \frac{V_i \angle \delta_i - V_j \angle \delta_j}{R_{ij} + jX_{ij}} \quad (1)$$

V_i is taken as the reference, and therefore the angle is shifted into 0. The apparent power at bus 2 can be written as;

$$S_i = V_i I^* \quad (2)$$

Rearranging (2) yields;

$$I = \left(\frac{S_i}{V_i} \right)^* \quad (3)$$

$$I = \frac{P_j - jQ_j}{V_j \angle \delta_j} \quad (4)$$

Equating (1) and (4) we obtained,

$$\frac{V_i \angle \delta_i - V_j \angle \delta_j}{R_{ij} + jX_{ij}} = \frac{P_j - jQ_j}{V_j \angle \delta_j} \quad (5)$$

Separating the real and imaginary parts yields,

$$V_i V_j \cos \delta_{ij} - V_j^2 = R_{ij} P_j + X_{ij} Q_j \quad (6)$$

And,

$$-V_i V_j \sin \delta_{ij} = X_{ij} P_j - R_{ij} Q_j \quad (7)$$

Rearranging (7) for P_j and substituting into (6) yields a quadratic equation of V_j ;

$$V_j^2 - \left(\frac{R_{ij}}{X_{ij}} \sin \delta_{ij} + \cos \delta_{ij} \right) V_i V_j + \left(X_{ij} + \frac{R_{ij}^2}{X_{ij}} \right) Q_j = 0 \quad (8)$$

The roots for V_j will be;

$$V_j = \frac{\left[\frac{R_{ij}}{X_{ij}} \sin \delta_{ij} + \cos \delta_{ij} \right] V_i \pm \sqrt{\left[\left(\frac{R_{ij}}{X_{ij}} \sin \delta_{ij} + \cos \delta_{ij} \right) V_i \right]^2 - 4 \left(X_{ij} + \frac{R_{ij}^2}{X_{ij}} \right) Q_j}}{2} \quad (9)$$

To obtain real roots for V_j , the discriminate is set greater than or equal to '0'; i.e.:

$$\frac{\left[\left(\frac{R_{ij}}{X_{ij}} \sin \delta_{ij} + \cos \delta_{ij} \right) V_i \right]^2 - 4 \left(X_{ij} + \frac{R_{ij}^2}{X_{ij}} \right) Q_j \geq 0}{\frac{4Z_{ij}^2 Q_j X_{ij}}{(V_i)^2 (R_{ij} \sin \delta_{ij} + X_{ij} \cos \delta_{ij})^2} \leq 1} \quad (10)$$

Since δ_{ij} is normally very small then,

$\delta_{ij} \approx 0$, $R_{ij} \sin \delta_{ij} \approx 0$, and $X_{ij} \cos \delta_{ij} \approx X_{ij}$

Taking the symbols 'i' as the sending bus and 'j' as the receiving bus. Hence, the fast voltage stability index, FVSI can be defined by:

$$FVSI_{ij} = \frac{4Z_{ij}^2 Q_j}{V_i^2 X_{ij}} \quad (11)$$

Where: Z_{ij} = line impedance

X_{ij} = line reactance

Q_j = reactive power at the receiving end

V_i = sending end voltage

The value of FVSI that is evaluated close to 1.00 indicates that the particular line is closed to its instability point which may lead to voltage collapse in the entire system. To maintain a secure condition the value of FVSI should be maintained well less than 1.00.

B) 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 particular, 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, Fig.1. 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).

3. Material and Method

A) RBFNN Model for FVSI

Several types of ANN structures and training algorithms have been proposed. 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 directly for 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 are summarized by the following steps:

- A set of realistic system loading patterns a regenerated by varying the real power and reactive power loadings at various line outages and for various reactive power control variables and loading conditions.
- For each of the loading patterns generated in step (a) the load flow and modal analysis of the reduced Jacobian matrix are done and FVSI was calculated for each line in the system to identify the most vulnerable few load buses from the voltage stability point of view.
- The RBFNN is designed and trained by the input patterns (V_b , δ_b , P_b , Q_b) for each bus is generated as shown in Fig.4.

d. The RBFNN, the target output is FVSI to show distance to voltage collapse for each input pattern is computed by running the contour program.

e. Finally, training of these RBFNN using the input/output patterns developed in Steps 3 and 4 is carried out.

B) Iraqi super grid network

The transmission level in the Iraqi electrical network consists of the 400KV 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 400KV 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 3664.6Km) and configuration of this network shown in Fig.2.

4. 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. For generating training data for the RBFNN, active and reactive power set the load buses are varied within 5, 10, 15, 20, and 25% of the base case values. For each operating condition, bus operating parameter selected transmission lines are recorded as the input features. Contingency analysis is performed for all line outages and the MW margins to voltage instability are recorded by using Matlab 10 and table (1, 2) shows the bus data and transmission line data. A flow chart describing the modal analysis procedure adopted is presented in Fig.5. The experiment results were used to train the neural network which have been constructed and trained using 135 data samples from the experimental data and 16 samples were used for generalization test of the trained neural network.

From the analysis of the results in Table 3 show the FVSI for five load change. As mentioned above that system will unstable when FSVI near to 1 therefore it is clear that the system is unstably with increasing the load change and increasing of FSVI depend on the bus type for example the Transmission line connect to Gen. Bus or Reference bus are more stable because they near to source. In addition, for a given operating condition, the most critical transmission line in the system has been identified and appropriate algorithms i.e. TL_{6-15} is unstable under 25% load change.

From the analysis of the results in Table 4, it is observed that the accuracy of the RBFNN method was slightly superior when compared to the CFVSI on account of both maximum error and mean average error (MAE) for both load change.

5. Conclusion

In this study voltage stability assessment of power systems by using RBFNN has been explored, and this was obvious from the generalization test. The simulation data from FVSI 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 FVSI between prediction by RBFNN and CFSVI 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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Table 1. Bus data for Iraq Super Grid

Bus No.	Bus Code	Bus Voltage	Bus Angle	Load MW	Load Mvar	Gen MW	Gen Mvar
1	1	1.025	0	0	0	0	0
2	2	1	-6.422	0	0	998	0
3	0	0.9872	-36.681	776.24	274.967	0	0
4	2	0.99	-36.664	0	0	956	0
5	2	1	-43.189	173.326	61.1221	260	0
6	0	0.951	-57.640	672.525	284.514	0	0
7	0	0.980	-61.037	0	0	0	0
8	0	0.972	-61.892	963.482	349.459	0	0
9	0	0.982	-61.661	533.953	184.268	0	0
10	2	0.99	-61.705	0	0	0	0
11	0	0.976	-61.567	124.763	53.8677	0	0
12	0	0.956	-59.090	64.2869	173.375	0	0
13	0	0.972	-60.382	105.411	20.2787	0	0
14	0	0.934	-88.740	340.817	109.199	0	0
15	2	1	-49.758	254.445	72.1922	0	0
16	0	0.994	-51.535	129.545	41.4657	0	0
17	2	1	-60.064	214.376	68.0632	1200	0
18	2	1	-59.904	0	0	500	0
19	0	0.991	-62.103	401.600	77.3193	0	0
20	0	0.976	-65.806	264.633	183.590	0	0
21	2	1	-79.779	457.697	221.117	840	0
22	0	0.957	-94.941	319.107	168.702	0	0
23	2	0.99	-94.286	177.971	88.0291	400	0
24	2	1	-94.710	742.511	262.080	0	0

Table 2. Transmission Line for Iraqi Super Grid

Bn1	Bnr	Rline	Xline
1	2	0.00072	0.005885
2	3	0.0021	0.017185
3	4	2.00E-05	0.0002
3	6	0.002415	0.021965
3	15	0.00345	0.03132
4	5	0.0018	0.01635
5	13	0.004247	0.038612
6	9	0.00093	0.00847
6	12	0.000616	0.005608
6	15	0.00485	0.04405
7	11	0.000215	0.00197
7	12	0.000964	0.008772
7	17	0.00122	0.01015
7	18	0.001094	0.009106
7	20	0.00308	0.02795
8	9	0.00029	0.00262
8	11	0.00041	0.003745
8	13	0.000435	0.00394
9	10	7.50E-05	0.00069
11	14	0.02744	0.22904
14	21	0.00432	0.03928
14	22	0.00479	0.04354
15	16	0.00292	0.02391
17	18	0.000125	0.001043
17	19	0.000405	0.003365
19	20	0.001165	0.009675
20	21	0.00383	0.03485
21	24	0.00439	0.03993
22	23	0.00145	0.0132
23	24	0.00059	0.00538

Table 3. FVSI for five steps load change

Load Change	5% load	10% load	15% load	20% load	25% load
1	-0.02928	0.029523	0.05396	0.054856	0.056353
2	-0.26344	-0.27432	-0.291	-0.31469	-0.34741
3	0.006403	0.007643	0.010081	0.014095	0.020486
4	-0.48051	-0.50529	-0.53133	-0.55882	-0.58809
5	0.147592	0.26318	0.392607	0.53882	0.706606
6	0.085468	0.166893	0.256578	0.355925	0.467017
7	-0.03611	-0.03783	-0.03955	-0.04127	-0.04299
8	-0.05673	-0.06099	-0.06559	-0.07058	-0.07607
9	-0.04877	-0.05244	-0.05639	-0.06068	-0.06541
10	0.221753	0.397349	0.596469	0.825077	1.092725
11	-0.00503	-0.00533	-0.00565	-0.00597	-0.00631
12	-0.07227	-0.0766	-0.08108	-0.08573	-0.0906
13	0.097303	0.141227	0.189549	0.243011	0.303139
14	0.047124	0.071517	0.098034	0.127058	0.159348
15	-0.25074	-0.26294	-0.27559	-0.28876	-0.30258
16	-0.01686	-0.018	-0.0192	-0.02046	-0.02178
17	-0.0097	-0.01036	-0.01105	-0.01178	-0.01254
18	-0.00387	-0.00414	-0.00441	-0.0047	-0.005
19	0.024478	0.025135	0.026291	0.028054	0.030616
20	-2.11093	-2.19694	-2.28684	-2.3812	-2.48112
21	0.24773	0.360203	0.488359	0.634559	0.834146
22	-0.63028	-0.65967	-0.69051	-0.72298	-0.76485
23	-0.04077	-0.04271	-0.04465	-0.04659	-0.04853
24	0.005207	0.007812	0.010576	0.013527	0.016722
25	-0.01176	-0.01232	-0.01288	-0.01344	-0.014
26	-0.08505	-0.08839	-0.09178	-0.09521	-0.09871
27	0.200307	0.289762	0.390785	0.505018	0.653784
28	0.363884	0.384151	0.405753	0.428776	0.754945
29	-0.02122	-0.00687	0.008332	0.024468	-0.07312
30	0.050021	0.052807	0.055776	0.058941	0.105906
Max. FVSI	0.363884	0.397349	0.596469	0.825077	1.092725

Table 4. Comparison between CFVSI and RBFNN for 5, 25 % load change

Load Change	Conventional FVSI		RBFNN-FSVI		Error	
	5% Load	25% load	5% load	25% load	Error 5%	Error 25%
1	-0.02928	0.056353	-0.02455	0.06196	0.047241	0.056073
2	-0.26344	-0.34741	-0.26045	-0.34659	0.029812	0.008164
3	0.006403	0.020486	0.012300	0.02305	0.058969	0.02564
4	-0.48051	-0.58809	-0.47611	-0.57854	0.043949	0.095552
5	0.147592	0.706606	0.14810	0.714054	0.005163	0.074476
6	0.085468	0.467017	0.08567	0.47178	0.002033	0.047627
7	-0.03611	-0.04299	-0.03458	-0.04008	0.015268	0.029092
8	-0.05673	-0.07607	-0.04834	-0.07079	0.083786	0.052825
9	-0.04877	-0.06541	-0.04508	-0.05959	0.036912	0.058202
10	0.221753	1.092725	0.22698	1.094931	0.052284	0.022061
11	-0.00503	-0.00631	0.00144	0.000586	0.064787	0.068951
12	-0.07227	-0.0906	-0.07183	-0.08733	0.004274	0.032619
13	0.097303	0.303139	0.10248	0.307986	0.051774	0.048462
14	0.047124	0.159348	0.04795	0.166177	0.008305	0.068299
15	-0.25074	-0.30258	-0.24672	-0.29906	0.040145	0.035181
16	-0.01686	-0.02178	-0.00884	-0.01788	0.08011	0.039044
17	-0.0097	-0.01254	-0.00203	-0.00537	0.076634	0.071709
18	-0.00387	-0.005	0.002518	-0.00135	0.063913	0.036528
19	0.024478	0.030616	0.03245	0.039859	0.079811	0.092438
20	-2.11093	-2.48112	-2.10326	-2.48029	0.076653	0.008266
21	0.24773	0.834146	0.25051	0.842448	0.027813	0.083025
22	-0.63028	-0.76485	-0.62799	-0.76041	0.022801	0.044388
23	-0.04077	-0.04853	-0.03977	-0.04169	0.009908	0.068407
24	0.005207	0.016722	0.00791	0.018799	0.027112	0.020777
25	-0.01176	-0.014	-0.01043	-0.01393	0.01326	0.000631
26	-0.08505	-0.09871	-0.07843	-0.08891	0.06612	0.097965
27	0.200307	0.653784	0.21012	0.662961	0.098187	0.091776
28	0.363884	0.754945	0.37157	0.758552	0.076918	0.036073
29	-0.02122	-0.07312	-0.01831	-0.06618	0.029043	0.069436
30	0.050021	0.105906	0.05470	0.107131	0.046892	0.012251
				Max. Error	0.044663	0.049865
				MAE	0.098187	0.097965

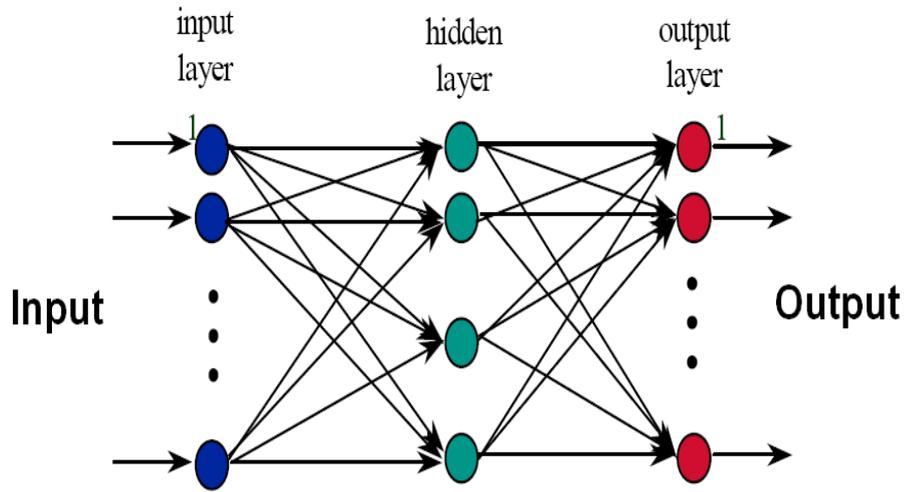


Figure 1. Radial Basis Function Neural Networks

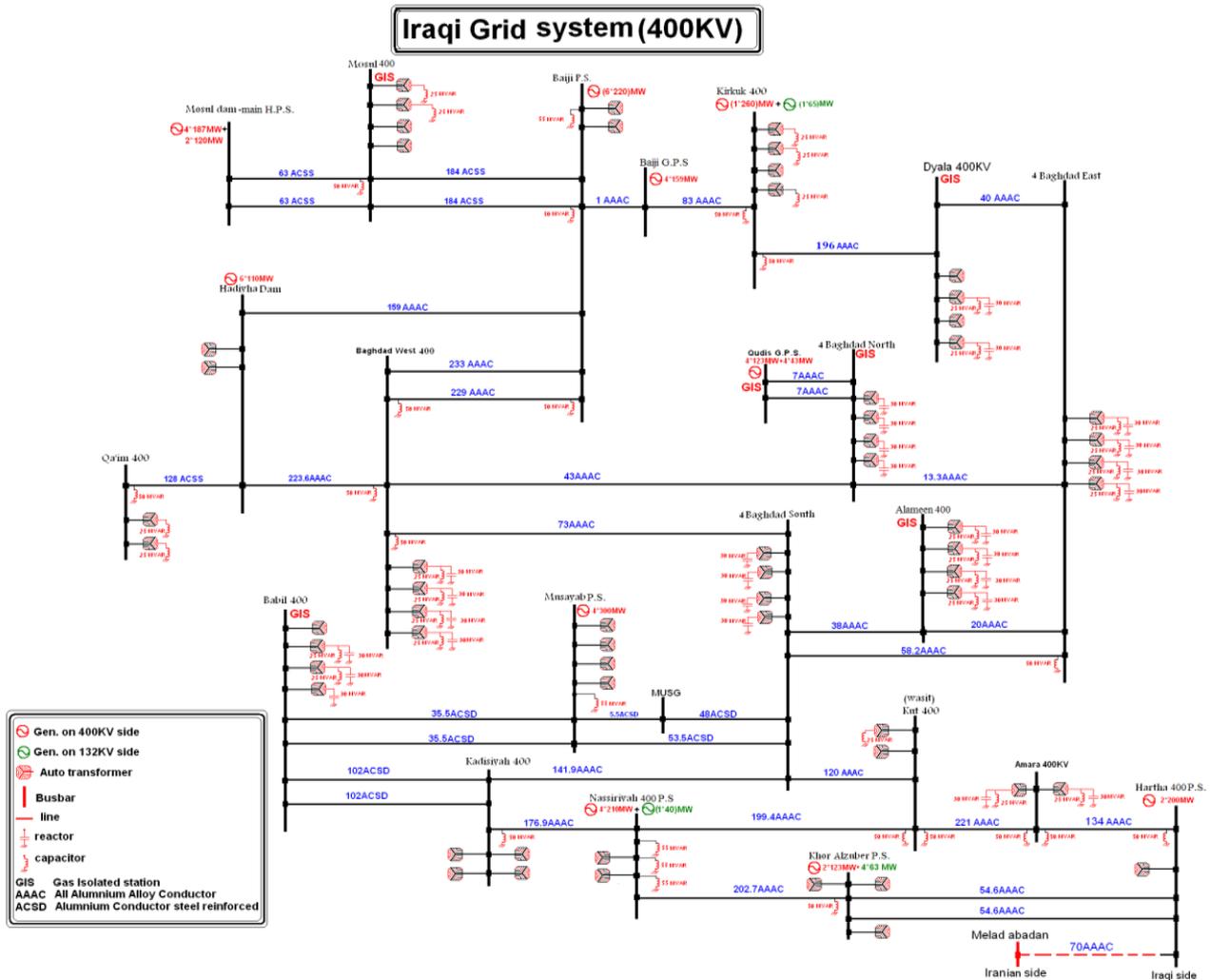


Figure 2. Iraqi super Grid network, 400KV

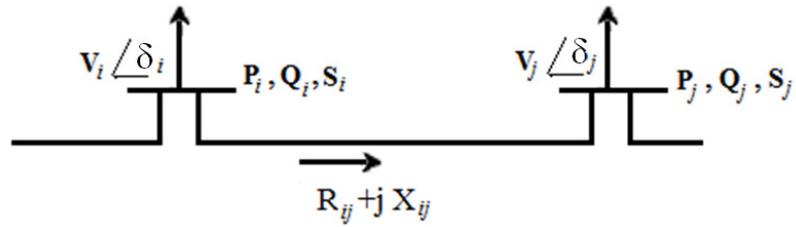


Figure 3. General Bus Power System Model

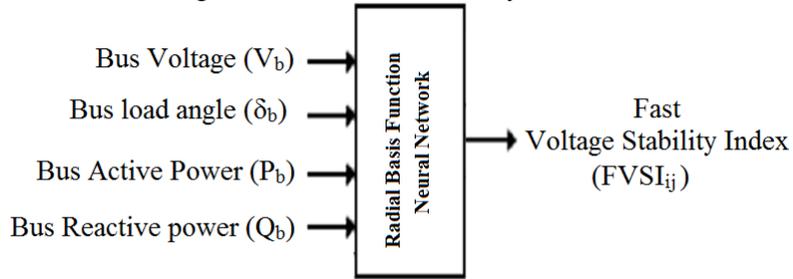


Figure 4. RBFNN FVSI Predication model

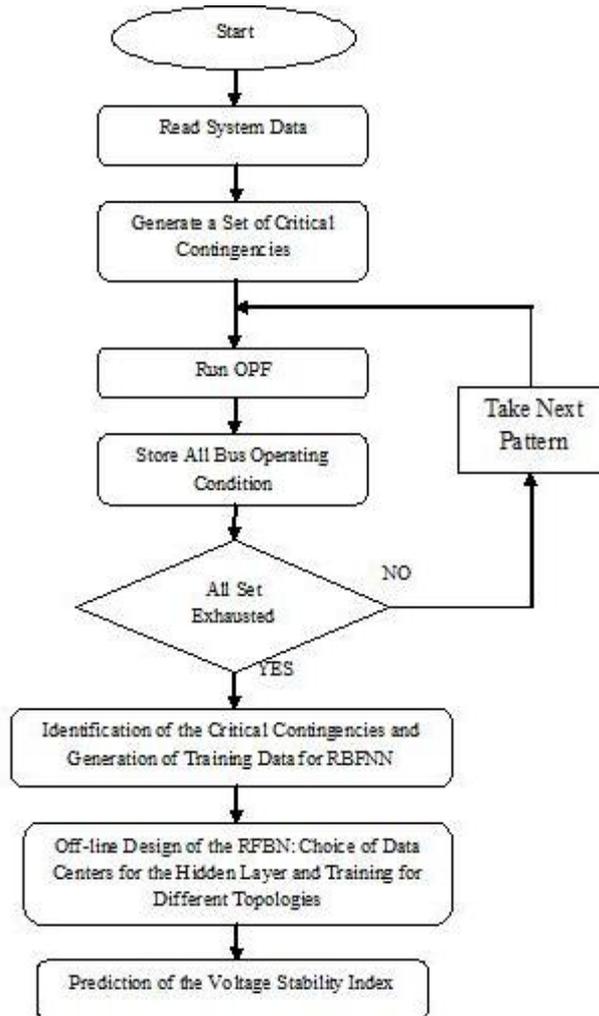


Figure 5. Online voltage stability monitoring algorithm