Improvement of Voltage Stability in Interconnected Power Systems Using a Neural Network

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Abstract: This paper provided a method for improvement of voltage stability in interconnected power systems using a neural network, this is because the present power systems is a complex network consisting of several sub-networks such as generation, transmission and distribution. Use of new technologies and the growth in Interconnections are continuously increasing the complexity of the system. These highly complex modern power systems operate in severely stressed conditions due to economical and environmental considerations rendering them vulnerable to frequent failures. Therefore, ensuring the stability of these systems has become one of the major concerns for the power engineers, especially the voltage stability. In this paper deals with critical buses to calculate the stability margins and the outputs of this technique are used to train and test the neural network. The trained NN architecture is capable of reducing the error values to acceptable value of about 5%. This method is applied on an *IEEE-14 bus system*.

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1. Introduction

Power System Stability may broadly be defined as the ability of a power system to remain in a state of operating equilibrium during normal operating conditions and to regain an acceptable state of equilibrium after being subjected to a disturbance. There are three types of stabilities viz. rotor angle stability, frequency stability and voltage stability. Voltage Stability is load stability concerned with load area and load characteristics. Rotor angle stability is basically generator stability concerned with integrating remote power plants to a large system over long transmission lines. Voltage stability is the ability of a power system to achieve or maintain the voltage magnitudes at acceptable levels at all buses in the system during faults, disturbances, and stressed conditions.

A system enters a state of voltage instability when a disturbance, increase in load demand, or change in system condition causes a progressive and uncontrollable drop in voltage. The main factor for instability is the inability of the power system to meet the demand of increased reactive power. It is essentially a local phenomenon but may have widespread impact and often lead to voltage collapse. Since 1970, many instances of voltage collapse have been witnessed globally, making voltage stability one of the major issues in power system planning, operation and control. In this paper, ANN is used to check voltage stability margins. The results of this technique are verified by using active and reactive power for critical buses. The results obtained are used to train a feed-forward neural network using the back propagation algorithm [1, 2].

1. Voltage Stability and Voltage Collapse

The problem of voltage stability may be simply explained as inability of the power system to provide the reactive power or the egregious consumption of the reactive power by the system itself. It is understood as a reactive power problem and is also a dynamic phenomenon. Voltage stability is the ability to transfer reactive power from production sources to consumption sinks during steady state [3, 4] .

A power system at given operating state undergoes voltage collapse if post disturbance equilibrium voltage is below acceptable limits.

In recent years, the analysis of voltage stability has assumed importance, mainly due to several documented incidents of voltage collapse in France, Japan, Belgium and Florida.

Several factors contribute to voltage collapse such as increased loading on transmission lines, reactive power constraints, on-load tap changer (OLTC) dynamics and load characteristics.

Voltage instability implies an uncontrolled decrease in voltage triggered by a disturbance, leading to voltage collapse and is primarily caused by dynamics connected with the load [5].

Voltage Security means the ability of a system no only to operate in a stable manner but also to remain stable following credible contingencies, load increases, or existence of considerable margin from operating point to voltage stability point.

There are two types of voltage stability based on the time frame of simulation: static voltage stability and dynamic voltage stability. Static analysis involves only the solution of algebraic equations and therefore is computationally less extensive than dynamic analysis. Static voltage stability is ideal for the bulk of studies in which voltage stability limit, for many pre-contingency and post-contingency cases, must be determined.

In static voltage stability, slowly developing changes in the power system occur that eventually lead to a shortage of reactive power and declining voltage. This phenomenon can be seen from the plot of the power transferred versus the voltage at receiving end. The plots are popularly referred to as P-V curve or “Nose” curve. As the power transfer increases, the voltage at the receiving end decreases. Eventually, the critical (nose) point, the point at which the system reactive power is short in supply, is reached where any further increase in active power transfer will lead to very rapid decrease in voltage magnitude. Before reaching the critical point, the large voltage drop due to heavy reactive power losses can be observed. The only way to save the system from voltage collapse is to reduce the reactive power load or add additional reactive power prior to reaching the point of voltage collapse [6].

Voltage collapse phenomena in power systems have become one of the important concerns in the power industry over the last two decades, as this has been the major reason for several major blackouts that have occurred throughout the world including the recent Northeast Power outage in North America in August 2003 [7]. Point of collapse method and continuation method are used for voltage collapse studies [8]. Of these two techniques continuation power flow method is used for voltage analysis. These techniques involve the identification of the system equilibrium points or voltage collapse points where the related power flow Jacobian becomes singular [9, 10].

Usually, placing adequate reactive power support at the “weakest bus” enhances static-voltage stability margins. The weakest bus is defined as the bus which is nearest to experience a voltage collapse.

2. Neural Network

Artificial neural systems have been studied for many years in the hope of achieving human-like performance in thinking and evaluation. These systems (ANSs) are mathematical models of theorized mind and brain activities. ANSs are also referred to as neural networks.

Processing elements (PEs) also referred to as nodes. The input signals come from either the environment or outputs of other PEs. Each connected pair of PEs is an adjustable value called weight. Four common threshold functions used in processing elements: these threshold functions are the linear, ramp, step and sigmoid.

A field that receives input signals from the environment is called an input field (input layer), and a field that emits signals to the environment is called an output field (output layer), any field that lies between the input and output field is called hidden fields (hidden layer) and has no direct field contact with the environment (i.e. no contact with input and output PEs).

So, an artificial neural network is formed of an input layer (input variables), a hidden layer (consists of artificial neurons for estimation of voltage stability margins) and an output layer (number of neurons in output layer is determined by the number of neuron outputs). Backprobagation networks often use the tan-sigmoid transfer function.

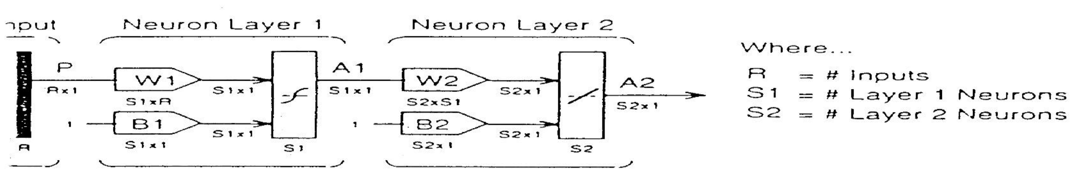

Fig.1. Network architecture

4. Application of ANN on Voltage Stability

In this paper the IEEE 14-bus system is studied using ANN, This system is studied using Q-V curves, method to determine weak buses leading to bus 12, bus l3, and bus 14, as the weakest ones.

According to the output of load flow result, the real and reactive loads at these buses are used as inputs to the ANN, beside the total system load levels. However, distribution of the total load among load buses may change during load cycles or during tough weather conditions where mainly the air conditioning load area consumes most of the total power. There are two approaches to take these different factors into account.

(1) Constant Participation Factors

Each bus i has reactive power load of Q_i, and active load of P_i

$\beta_i = Pi/P_L$ (1)

Where: β_i, is active power participation factor of bus i

P_L is the system total power load

$\gamma_i = Q_i / Q_L$ (2)

Where: γ_i is reactive power participation factor of bus i

Q_L is the system total reactive load

These factor values can be estimated by heuristic knowledge of the system conditions and how the load is usually distributed during a load cycle. Values will be considered during analysis of the system [11].

(2) Looking at Critical Buses only

Since voltage stability is greatly affected by critical load buses, i.e. the system may be lightly loaded relative to its capability, but critical buses are highly loaded causing stability problems. A certain bus is judged as a critical bus by many methods such as Q-V curves, and Q-V Sensitivity.

(3) Combining the Two Factors

This paper takes the advantages of both the two preceding approaches, and will, be used in training ANN in the following sections however; the problem will be more complex and not easy to be recognized by the ordinary ANN.

5. Obtaining Data Set

In order to train and test the neural network we must obtain a wide range of operating conditions and their corresponding stability indices (data set).The algorithm used to obtain data set is as follow:

1) Assuming certain load levels Q_L and P_L say 1.2p.u.
2) Each bus's real and reactive load is calculated using its participation factors $\beta_j$and γ_j .
3) Exact real and reactive load at critical buses (which may differ slightly form the value calculated by step 2, but they greatly affect stability) are used in calculation.
4) Critical buses reactive margins are calculated using Q-V curves. This algorithm is repeated to obtain a wide range of operating conditions. In our case, load level in step 1 is changed from 0.7 p.u to 1.8 p.u. Real and reactive load of critical buses is changed from the value calculated by step 2 in 0.05 p.u above and 0.05 p.u below to have three points at each load level. This led to obtain 36 operating conditions to be used in training. There are also many operating conditions chosen randomly will be used to test classify trained Neural net.

6. Structure of the Neural Network

The back propagation network is the most suitable network for our problem. The network is y Matlab Neural Tool Box [12]. It possesses the following features:

1. An input layer with tan sigmoid threshold function of 7 inputs, they are total system load level, and reactive and active power loads at the three critical buses 12, 13, 14. The number of hidden neurons in this layer is optional and there is no straightforward form to determine it, each problem must be checked with different numbers of hidden neurons, to know the optimum number which leads to the least error. Hidden neurons (6, 7, 8) will be checked.
2. Output layer with linear threshold function has 3 neurons. This number is determined by the number of outputs which is 3. These are the three buses reactive margin M_{14}, M_{13}, and M_{12}.
3. The starting values of weights and biases are generated by a random function that exists in the tool box. Since the training time is greatly affected by the starting values of weights and biases, the tool box already contains another function used to generate these starting values especially for back probagation net leading to a short training time.
4. Learning rate is 0.01.
5. During training phase of Neural net weights, biases are continuously updated so that the some square error (SSE) between the computed values of outputs through the network weights and biases, and the outputs supplied with the training data set is minimum. As this threshold is reduced, the network factors will adjust the net to fit the training data perfectly.
6. Maximum number of training cycles (epochs) is set to be 100000.

7. Case study

In this case the application of IEEE 14 bus system is discussed see Figure (2). Using active and reactive power at critical buses 12,13,14 beside total system load level as an inputs (input layer), and desired output allowing the artificial neural network to train the network and test it to reduce the error values to acceptable value say 5%.

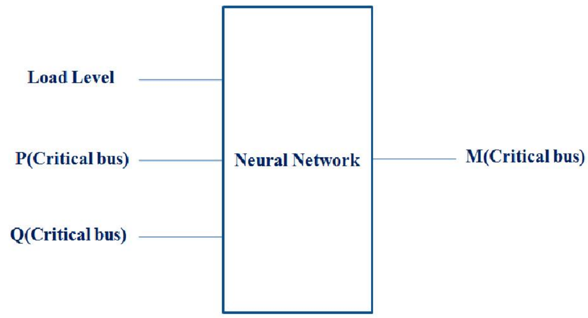

Fig.2. inputs and outputs for Neural Network architecture

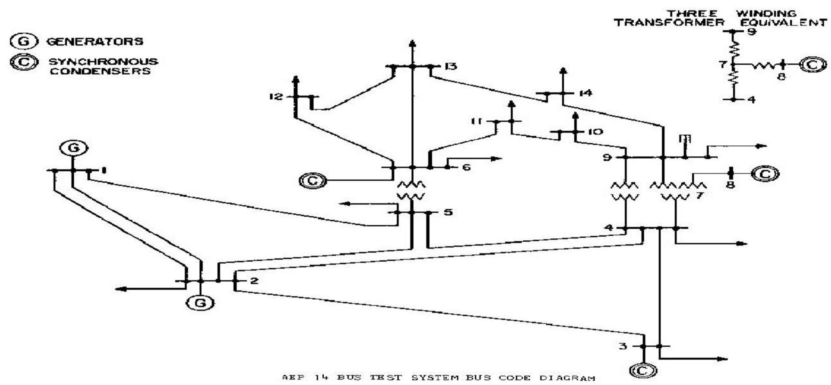

Fig. 3. Single line diagram for IEEE 14 Bus Network

Table (1) gives us the classifying data sets for training the neural network on 36 operating conditions.

Load level	P14	Q14	P13	Q13	P12	Q12	Margin14	Margin13	Margin12
0.7	0.104	0.035	0.097	0.0406	0.0426	0.01116	0.82	0.955	0.79
0.7	0.154	0.085	0.147	0.0906	0.0936	0.06116	0.725	0.845	0.665
0.7	0.204	0.135	0.197	0.146	0.1426	0.111	0.6	0.685	0.542
0.8	0.1191	0.04	0.111	0.0461	0.0487	0.0127	0.812	0.949	0.762
0.8	0.1691	0.09	0.161	0.0964	0.0987	0.0627	0.692	0.8	0.6375
0.8	0.2191	0.14	0.211	0.1464	0.1487	0.1127	0.563	0.633	0.5057
0.9	0.134	0.045	0.1249	0.0522	0.0548	0.01435	0.7734	0.9095	0.7287
0.9	0.184	0.095	0.1749	0.1022	0.1048	0.0643	0.652	0.7523	0.6025
0.9	0.234	0.145	0.2249	0.1522	0.1548	0.1143	0.515	0.578	0.466
1	0.1488	0.05	0.138	0.058	0.06	0.0159	0.733	0.8625	0.6935
1	0.1988	0.1	0.188	0.108	0.11	0.0659	0.632	0.701	0.567
1	0.2488	0.15	0.238	0.158	0.16	0.1159	0.467	0.523	0.424
1.1	0.16378	0.055	0.1526	0.0638	0.067	0.0175	0.6941	0.8125	0.659
1.1	0.2137	0.105	0.2026	0.1138	0.117	0.0675	0.5643	0.6445	0.5252
1.1	0.2637	0.155	0.2526	0.1638	0.167	0.1175	0.417	0.4575	0.3775
1.2	0.1786	0.06	0.1665	0.0696	0.0731	0.0191	0.6496	0.7585	0.6201
1.2	0.2286	0.11	0.2165	0.1196	0.1231	0.0691	0.5143	0.5846	0.4816
1.2	0.2786	0.16	0.2665	0.1696	0.1731	0.1191	0.3576	0.385	0.326

Table (1) The classifying data sets for training the neural net on 36 operating conditions (Continued).

Load level	P14	Q14	P13	Q13	P12	Q12	Margin14	Margin13	argin12
1.3	0.1935	0.065	0.18	0.075	0.079	0.0207	0.6025	0.7	0.5785
1.3	0.2435	0.115	0.23	0.125	0.129	0.0707	0.4582	0.5173	0.4335
1.3	0.2935	0.165	0.28	0.175	0.179	0.1207	0.2815	0.3054	0.2666
1.4	0.2084	0.07	0.19429	0.08	0.0853	0.0223	0.5467	0.6342	0.5325
1.4	0.2584	0.12	0.2442	0.13	0.1353	0.0723	0.3852	0.4332	0.3785
1.4	0.3084	0.17	0.19429	0.181	0.1853	0.1223	0.1883	0.201	0.1832
1.5	0.2233	0.075	0.2081	0.087	0.0914	0.02391	0.4763	0.5495	0.4797
1.5	0.2733	0.125	0.2581	0.137	0.1411	0.0739	0.2995	0.3325	0.3
1.5	0.3233	0.175	0.3081	0.187	0.1914	0.1239	0.074	0.0763	0.0727
1.6	0.2382	0.08	0.222	0.0928	0.0975	0.0255	0.395	0.4502	0.404
1.6	0.2582	0.1	0.242	0.1128	0.1175	0.0455	0.3203	0.3596	0.3282
1.6	0.2882	0.13	0.272	0.1428	0.1475	0.0755	0.1952	0.2116	0.1993
1.7	0.2531	0.085	0.2359	0.0986	0.103	0.027	0.2942	0.3323	0.3076
1.7	0.2731	0.105	0.2559	0.1186	0.1236	0.0471	0.2082	0.2282	0.2172
1.7	0.3031	0.135	0.2859	0.1486	0.1536	0.0771	0.0572	0.0599	0.0592
1.8	0.268	0.09	0.2498	0.1045	0.1097	0.0287	0.1607	0.1737	0.1702
1.8	0.288	0.11	0.2698	0.1245	0.1297	0.0487	0.0527	0.055	0.0555
1.8	0.298	0.12	0.2798	0.1345	0.1397	0.0587	0.0	0.0	0.0

After training of the network we must test it to insure that the network will act well when it is required to classify new cases, the network never trained on it. In our case we will test the network by 5 cases, these cases weren't supplied to the network in the training data, we will supply the network with the inputs for these cases, and the network will give us the outputs. These outputs, computed by the network, must be as close as possible to actual outputs, to judge the network as a good representative of the actual system.

8. Effect the Number of Hidden Neurons on Classifying New Case

Table (2) Testing data for Neural Network

Load level	P14	Q14	P13	Q13	P12	Q12	Margin14	Margin13	Margin12
1.05	0.1563	0.0525	0.1457	0.0609	0.0646	0.01674	0.7142	0.8377	0.6769
1.25	0.2861	0.1052	0.2734	0.1725	0.2762	0.12	0.331	0.3223	0.2661
1.45	0.2959	0.1325	0.2012	0.18417	0.16839	0.06311	0.2987	0.3281	0.3033
1.55	0.2307	0.0775	0.2151	0.0899	0.0944	0.0247	0.4368	0.5018	0.4448
1.65	0.2456	0.1225	0.2489	0.095	0.1805	0.0763	0.2223	0.2448	0.2216

Table (3) Output and Error of ANN Model 8 Neurons in Hidden Layer trained on (36) cases

Case no.	Computed Values of Outputs			The Error		
	M14	M13	M12	Δ M14	ΔM13	ΔM12
1	0.7204	0.8387	0.6868	0.0062	0.001	0.0099
2	0.3068	0.2994	0.2593	-0.0242	-0.0229	-0.0068
3	0.3019	0.3383	0.309	0.0032	0.0102	0.0057
4	0.4384	0.5031	0.4378	0.0016	0.0013	-0.007
5	0.1995	0.2154	0.1987	-0.0228	-0.0294	-0.0229

As the number of training cycles (epochs) increases the SSE value decreases then the value will settle regardless additional training cycles.

The different numbers of neurons in hidden layer has small effect on errors in the five classified cases. To overcome this problem the network structure will be improved in order to reduce the errors values to acceptable value say 5%.

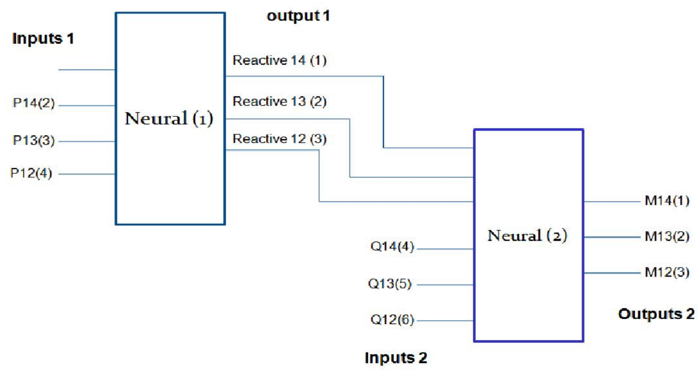

Fig.4. Connection Diagram for the Two Networks

The first network (Neural 1) is trained alone with 4 inputs and 3 outputs after the first network adjusted its weights and biases, the second network (Neural .2) is then trained with 6 inputs and 3 outputs. Each network uses Back propagation technique with 5 neurons in hidden layer. Table (4) lists the output of the new network architecture.

Table (4) New Architecture Network Outputs

Case no.	Computed Values of Outputs by ANN			The Error		
	M14	M13	M12	Δ M14	ΔM13	ΔM12
1	0.7193	0.8378	0.6745	0.0051	0.0001	-0.0024
2	0.3017	0.314	0.2658	-0.0293	-0.0083	-0.0003
3	0.3078	0.3368	0.2854	0.0091	0.0087	-0.0179
4	0.4426	0.5063	0.4484	0.0058	0.0045	0.0036
5	0.2261	0.2546	0.2546	0.0038	0.0098	0.0001

In this new structure the error is reduced significantly so the second model is the better for representing the system we are studying.

9. Conclusions

The main points which can be extracted from the paper are summarized as follows:

1. Voltage stability is greatly affected by load type; some loads types have high impact on the system voltage stability while others have less impact. The system can be stable or unstable if different loads types with the same amount are applied on it. Also, voltage stability is greatly affected by both system active and reactive power loads, but reactive load is strongly affecting the voltage stability.
2. The old methods can not provide a fast solution to the voltage stability problem well. Time is very critical to take fast action to save the system from collapse. Artificial intelligent can overcome the long time needed to the study of system voltage stability and provide fast online solution. The effort needed for application of Artificial intelligence is during training phase. Of the Artificial intelligence like Neural Network is very helpful in solving this problem especially when it is nonlinear. It solve long standing problems where conventional approaches have difficulty, takes a short time during giving accurate results.
3. The application of Neural Network requires studying the system globally, to determine the weakest area, to choose the inputs which can be regarded as good representative of the whole system from voltage stability viewpoint. Also, the outputs of the network can give us stability

indices that summarize the whole system voltage stability condition. Neural Network must be tested to prove its reliability in order to use it online monitoring.

4. The application of under-voltage load shedding, controlled system separation and adaptive or intelligent control are steps in this direction. The idea of load shedding scheme incorporates the security feature of voltage stability. Beside the load shedding scheme, some other countermeasures, for example generation rescheduling or managing reactive power resources can also be carried out.

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