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Contingency Ranking – An ANN Approach

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Abstract

Contingency ranking is performed to choose the contingencies that cause the worst effects on the system. Ranking by conventional techniques is time consuming and very tedious process. An alternative solution is the off line training and run time application of artificial neural networks. Therefore in this paper an Artificial Neural Network based approach is proposed for fast contingency ranking. A multi – layered ANN is trained using error Back Propagation Technique with the input data taken as the voltage, phase angles, active and reactive power values and output data as condition number obtained from off line load flow studies. The condition number reflects the severity of the contingency on the power system. This neural network structure is applied for contingency ranking of line outages in an IEEE 30 bus system and is found to produce almost accurate results for previously unseen line outages almost instantaneously.

Index Terms— Power systems, failure recovery, Contingency ranking. ANN-artificial neural networks

I INTRODUCTION

A power system in its steady state is said to be secure if the operational limits on its generator's outputs, transmission line power flows and bus voltages are not violated when a contingency like loss of a generator or a load, outage of a transmission line etc. takes place. Security control deals with an advance assessment whether the system will remain secure and if insecure then taking remedial measures so that the power system operation can be kept in the normal state without delay when the contingency actually occurs. The conventional approach for security control is to perform a load flow analysis assuming a contingency and then check for violation of the constraints. If the system is found insecure the load flow is repeated with the possible remedial measures until the system can be made secure. With the increase in system size, the dimensionality of the load flow analysis increases resulting in excessive number of iterations, CPU time and computer memory.

One of the ways to rank the contingencies is using condition number which measures the sensitivity of the Jacobian matrix to the stability of the system. It is a quick way to determine which of the contingencies should be taken care of first to cause the minimum damage to the power system. It reduces the computation time when applied in ANN thus giving a faster result.

In this paper, the condition numbers are used to rank the contingencies first by normal load flow solution techniques. Here Newton Raphson Algorithm is used for its faster and better convergence rate than other load flow solutions. Then the condition number was calculated for each of these line outages. All the contingencies are then fed into the input layer of the feed forward multilayer neural network with their voltage (V), phase angle (δ), active and reactive power (Pd and Qd) and the bus connectivity status of the power system. The output i.e the condition number for each of the line outage is also fed to the neural network to train it. The trained network is tested with the test values of contingencies and their condition number are checked at the output of the neural network. The condition numbers thus found are then ranked in order of their decreasing value thus ranking the contingencies from most severe to the least severe.

II PROBLEM FORMULATION

The power system is a very large and complex system, so the planning, operation and maintenance of such a system economically, and qualitatively involves large number of analysis and studies, such as load flow studies, sensitivity analysis, security analysis, contingency analysis etc. Of all these, contingency analysis plays an important role in planning and operation of the power system more reliably. Due to the complex network topology, various equipments and unpredictable loads, power system is always subjected to some kind of abnormalities such as faults, failures, overloading, under loading etc. These are altogether termed as ‘contingencies’ on the power system. These contingencies force the power system constraints to violate and these contingencies are random in nature, so a power system should be in such a state that even in the case of violations of constraints, the control action should be in a position to bring back the system variables within limits, and such a state in power system is referred as “correctively secured state”. The realization of this state of power system needs an analysis of various contingencies that occur on the system and its impact on the system. But due to the complexity of the power system, types of contingencies that occur are wide in nature and it is laborious to analyze for all such contingencies. So out of the known contingencies, the contingency which have the highest probability of occurrence and has the most considerable impact on the system are listed and ranks are assigned to each of them based on the severity of the impact on the system. This process is termed as 'contingency ranking'. There are many methods and techniques available for contingency ranking. Each of them has their own applications and limitations in ranking. In this paper the contingencies are ranked based on the Condition Number of the Jacobian matrix which is an indication of the singularity of the matrix and hence the existence of its inverse.

III CONDITION NUMBER ANALYSIS

The power flow computer program (commonly called load flow) is the basic tool that computes the voltage magnitude and angle at each bus in the power system under balanced steady state conditions. It also computes the real and reactive power flow for all equipments interconnecting the buses as well as the equipment losses. Out of the various methods available for carrying out the load flow analysis, Newton Raphson method is most widely used as its it is more faster reliable, accurate and requires less number of iterations for larger size systems when compared to other methods. If x_1, x_2 are the unknown variables and y_1 and y_2 are the specified quantities in a bus, the specified quantities can be expressed as a non – linear function of unknown variables as

$$y_1 = f_1(x_1, x_2) \quad ....\{1\}$$
$$y_2 = f_2(x_1, x_2) \quad ....\{2\}$$

If x_1^0 and x_2^0 are the assumed approximate initial solution and Δx_1^0 and Δx_2^0 are the corrections required for x_1^0 and x_2^0 for the next better solution then the non linear equations {1} and {2} can be expressed as

$$y_1 = f_1(x_1^0 + \Delta x_1^0, x_2^0 + \Delta x_2^0) \quad ....\{3\}$$
$$y_2 = f_2(x_1^0 + \Delta x_1^0, x_2^0 + \Delta x_2^0) \quad ....\{4\}$$

The above equation can be linearized about the initial guess by using Taylor's series expansion as

$$\Delta y_1 = \Delta x_1^0\left(\frac{\partial f_1}{\partial x_1}\right) + \Delta x_2^0\left(\frac{\partial f_1}{\partial x_2}\right) \quad ....\{5\}$$
$$\Delta y_2 = \Delta x_1^0\left(\frac{\partial f_2}{\partial x_1}\right) + \Delta x_2^0\left(\frac{\partial f_2}{\partial x_2}\right) \quad ....\{6\}$$

The equations {5} and {6} can be arranged in the matrix form as

$$\begin{pmatrix} \Delta y_1 \\ \Delta y_2 \end{pmatrix} = \begin{pmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \end{pmatrix} \begin{pmatrix} \Delta x_1^0 \\ \Delta x_2^0 \end{pmatrix} \qquad \text{....\{7\}}$$

where $\begin{pmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \end{pmatrix}$ is called as system Jacobian Matrix which is a square matrix. In the power system P and Q are the specified variables, V and δ are the unknown variables and the load flow Jacobian is J= $\begin{pmatrix} \frac{\partial P}{\partial V} & \frac{\partial P}{\partial \delta} \\ \frac{\partial Q}{\partial V} & \frac{\partial Q}{\partial \delta} \end{pmatrix}$. Hence the correction values for the assumed unknown values are given by

$$\begin{pmatrix} \Delta V \\ \Delta \delta \end{pmatrix} = J^{-1} \begin{pmatrix} \Delta P \\ \Delta Q \end{pmatrix} \qquad \text{....\{8\}}$$

The inverse of Jacobian matrix J^{-1} does not exist when the determinant of J matrix becomes zero (i.e singular matrix). Condition number is a measure of sensitivity of the matrix to numerical operation. A condition number of a non singular square matrix 'A' is defined as

Cond (A) = [[A][x][A^{-1}]]

where, any matrix norm can be used. It quantifies the sensitivity of the system to changes in data. A large condition number is indicative of an ill conditioned matrix, i.e the determinant of the Jacobian matrix will be closer to zero and hence load flow will not converge and system become insecure. When the system is having a lower condition number, the system is secure as the inverse of the Jacobian matrix exists. The major computational requirements for the determination of condition number are a few repeat solutions with the available factored load flow solutions. Hence the computation time is quite small. So in this paper, condition number is used for its less computation time which helps in predicting the contingency which has to be taken care of in the least time so that minimum damage is caused to the power system and its components.

IV ANN BASED CONTINGENCY RANKING

In this paper contingency ranking is done based on the condition number for various line outages. The conventional method of contingency ranking is time consuming as it involves repeat simulation. Hence to ease the heavy computational burden, ANN is used which has distinct characteristics of efficient computation and ease of knowledge acquisition.

The ANN acts as a black box, which produces and output vector given a set of input vectors. Here, the ANN predicts the condition number based on certain inputs and also indicates the severity of the contingencies based on the condition number.

The basic processing elements of neural networks are called neurons or nodes. Neurons act as summing and non – linear mapping junctions. They can be considered as threshold units that can be fired when their total input exceeds certain biased levels. These neurons are often organized in layers and feedback connections both within the layer and towards adjacent layers are allowed. Each connection strength is expressed by a numerical value called weight, which can be modified. The characteristics of neurons are specified and the initial weights and the training modes are chosen. Appropriate inputs are then applied to the network so that it can acquire knowledge from the environment. As a result of such exposure, the network assimilates the information that can be later recalled by the user.

Multilayered perceptron (MLP) network is used in this paper which consists of several neurons arranged in different layers. A neuron receives many different inputs and produces a single output. The value of this output depends upon the value of the inputs and on the value of adjustable internal weights. This serves as input to the neuron in the preceding layer. However, the inputs to first layer are input to MLP itself and the output from the last layer constitutes the MLP output. An MLP can operate in two modes, namely training and testing. In training mode, an input vector is presented to the network and corresponding output is computed. The evaluated output is compared with the desired output. The difference between evaluated and desired output is called error and is used to adjust the MLP weights so as to minimize the error. Pairs of input and output vectors are presented to MLP sequentially and weights are continuously adjusted. When the weights are acceptably low for all vectors in training set, training phase is terminated. This training procedure is of supervised type because desired output is known prior to the start of training. In testing mode, trained network is evaluated by test data. If the MLP is successfully trained with an adequate training set it can perform generalization which is the ability of MLP to respond correctly using its past experience to an input, which it has never seen before. MLP training is carried out by back propagation algorithm that is designed to minimize the mean square error between actual output of the feed forward network and desired output.

Adopted ANN Model

The proposed ANN model uses a four – layered network, which is trained by using error back propagation algorithm. The number of neuron in the layers is determined by experimentation with an object that the ANN learns and generalizes the situation. Each neuron of ANN uses a mapping or activation function. The activation function employed is a ‘sigmoidal function’ as it is continuous and differentiable throughout which is represented by

$$F[x] = \frac{1}{(1+e^{-x)}} \qquad ....\{9\}$$

Input layer

Power system states can be characterized either by the bus injection, bus voltages, network configuration or line power loss. Based on these the following are the neurons in the input layer of MLP

1. Voltage

Voltage stability is the ability of the system to maintain acceptable voltages at all buses in the system under normal operating conditions and after being subjected to a disturbance. Furthermore, voltage instability results in a progressive and uncontrollable decline of voltage. Therefore voltage profiles are direct indicators of voltage stability. Hence voltage magnitudes at all buses are part of the input.

2. Load Angle

Angle between two bus voltages is the load angle whose variation causes the real power of the system to vary. This variation causes line outage in the system because of increase in real power of the system and hence they form the part of the input.

3. Active and Reactive power of the load

With the increase in load, generation must corresponding increase to meet the increased demand. However, it is not possible to increase the reactive power generation in generators beyond an extent, as it will damage the field windings. Hence there is always a shortage in reactive power supply, which results in decrease in voltage. Cumulative decrease of voltage leads the system to voltage collapse. Hence active and reactive power of the load is used as additional information to be included in the input.

4. Line configuration.

The presence or absence of line is likely to take the system either towards or away from collapse point. Hence line configuration forms an integral part of the input data. 1 or 0 represents all lines present in the system, where 0 indicates the occurrence of an outage and line being removed, while 1 indicates the presence of the line.

Hence, the input vector of the neural network comprise of

P = [V_1, V_2…..V_n, δ_1, δ_2…..δ_n, P_{d1}, P_{d2}…..P_{dn}, Q_{d1}, Q_{d2}….Q_{dn}, 1 or 0…..p times]

Where
n is the number of buses in the power system
V is the voltage of each bus
δ is the phase angle or load angle
P_d is the active power of the load
Q_d is the reactive power of the load

p is the number lines connecting the two buses

Various line outages consisting of single line, double line, triple line, four line and five line outages were used to train the MLP to give accurate values of condition number for any line outage given to them.

Hidden layer

There are no rules for the selection of the number of hidden layers and the number of neurons in each layer and is upto the designer. While in general, the more neurons in middle layer, the better the network can fit the target; too many neurons in middle layer can result in over fitting. The choice of number of neurons in the middle layer is based on experimentation and simulation. The number of hidden layers in the proposed model is two, hidden layer 1(H1) and hidden layer 2(H2). The number of neurons in each of them are 70 and 28 respectively to give an accurate converging solution.

Output layer

The output vector [q] of proposed ANN contains on element, the condition number.

Selection of training patterns

The training set is the representative of the different operating states of the power system. Offline power calculation results are used to construct the training set.

Training parameters

The maximum number of epochs is an important parameter towards training ANN. The number of training epochs and training time of ANN depends on the size of the power system. Another vital parameter is the learning rate. Usually, the learning rate is a small number so that the network will settle to a solution. Small value of learning rate means that the network has to make large number of iterations. It is possible increase the learning rate as learning proceeds. Increasing the learning rate as the network error decreases will often help to speed up convergence by increasing the step size as the error reaches a minimum. But if the learning rate is large, then network may bounce around too far from the actual minimum value.

V RESULTS AND OBSERVATIONS

An IEEE 30 – bus system was taken as the sample system for the study. The line outages for various possible contingencies are identified (a total of 36 line outages as in Table 5.1) and the condition numbers for each of these line outages were obtained.

TABLE 5.1: LIST OF CONTINGENCIES

Contingency No	Type of contingency	From Bus	To Bus
1	Normal	-	-
2	Single line outage	1	2
3	Single line outage	2	4
4	Single line outage	10	17
5	Single line outage	21	22
6	Single line outage	28	27
7	Double line outage	1 2	2 4
8	Double line outage	5 6	7 10
9	Double line outage	2 28	6 27
10	Double line outage	10 27	21 29
11	Double line outage	15 21	18 22
12	Triple line outage	1 2 2	2 4 6
13	Triple line outage	6 12 22	8 15 24
14	Triple line outage	2 12 29	6 16 30
15	Triple line outage	6 15 21	8 18 22
16	Triple line outage	6 10 25	10 20 27
17	Four line outage	6 14 10 27	9 15 22 29
18	Four line outage	5 10 14 8	7 17 15 28

19	Four line outage	6 12 18 24	7 14 19 25
20	Four line outage	6 10 12 25	10 20 15 27
21	Four line outage	2 9 10 27	4 10 17 29
22	Five line outage	2 99 16 10 23	6 10 17 22 24
23	Five line outage	6 10 12 18 24	7 21 14 19 25
24	Five line outage	2 6 4 15 15	5 9 12 18 23
25	Five line outage	2 5 9 10 27	4 7 10 17 29
26	Five line outage	5 4 8 19 14	7 12 28 17 15
27	Single line outage	1	3
28	Single line outage	9	10
29	Double line outage	2 2	4 5
30	Double line outage	23 27	24 30

31	Triple line outage	3 4 6	4 6 7
32	Triple line outage	4 12 28	6 15 27
33	Four line outage	3 4 6 12	4 6 9 14
34	Four line outage	9 16 10 23	10 17 22 24
35	Five line outage	2 6 14 10 27	4 9 15 22 29
36	Five line outage	2 4 6 18 15	6 12 28 19 23

The proposed neural network was trained by using the training patterns and error propagation algorithm. The training patterns are generated using 26 different contingencies (first 26). These contingencies are taken at random to train the ANN for all possible types of line outages i.e single line, double line, triple line, four line and five line outages

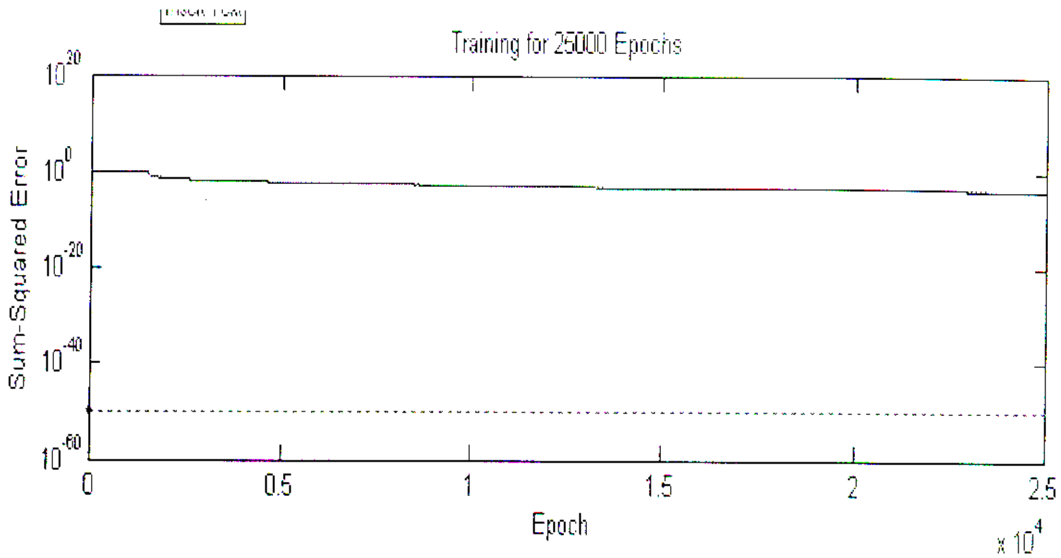
The total inputs to the ANN are 161, comprising 30 bus voltages, 30 phase angles, 60 active and reactive power of the load and 40 lines present in the system. In each hidden layer 70 and 28 neurons were found to be optimum. Hence the ANN structure for contingency ranking is 161-70-28-1

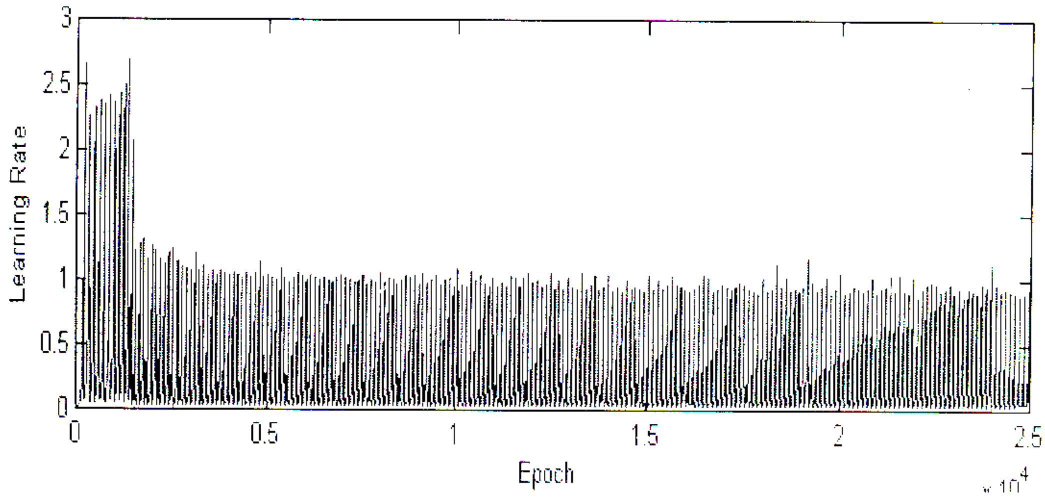
The training is carried out till error convergence is obtained. The performance of the trained neural network was tested on remaining 10 unseen patterns (last 10). The condition numbers found out after testing were ranked in order of their decreasing value from the most severe to the least. Satisfactory values of condition number are obtained after training the network as shown

TABLE 5.2: COMPARISION OF TARGET OUTPUT VALUES WITH ANN OUTPUT

Cont No	Target Cond No	ANN Cond No	Error	Tar-get Rank	ANN Rank
27	644.07	644.25	-2.3168	3	3
28	545.81	544.41	-1.3962	8	8
29	617.27	610.72	-6.5547	5	5
30	505.74	498.35	-7.3941	10	10
31	601.85	605.73	-3.8816	6	6
32	833.70	828.30	-5.4061	1	1
33	590.26	581.06	-9.1948	7	7
34	509.05	510.29	1.2334	9	9
35	635.299	640.17	4.8833	4	4
36	815.47	824.93	9.4639	2	2

The graph of epochs and the learning rate ANN is also shown for reference





VI CONCLUSION

Thus trained ANN model can be used to rank the contingencies based on the condition number so that computation time for ranking is much less when compared to the conventional methods and hence the remedial measures can easily be taken at the early stage to avoid system black out. The error between the target value and value found from the ANN model is about 2% only and hence nominal. This error can still be decreased by adding more number of neurons and hidden layers or by using some even more advanced training algorithm.

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