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Contingency Analysis of Power System Using Artificial Neural Networks

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Abstract— Contingency analysis is one of the most important tasks encountered by the planning and operation engineers of bulk power system. Power system engineers use contingency analysis to examine the performance of the system and to assess the need for new transmission expansions due to load increase or generation expansions. The different methods used for analyzing these contingencies are based on full AC load flow analysis or reduced load flow or sensitivity factors. But these methods need large computational time and are not suitable for on line applications in large power systems. It is difficult to implement on line contingency analysis using conventional methods because of the conflict between the faster solution and the accuracy of the solution. Therefore in this paper, computationally efficient method using artificial neural network is proposed for contingency analysis.

Index Terms—Contingency, Power flow study, artificial neural network.

◆

1 INTRODUCTION

Contingency analysis and risk assessment are important tasks for the safe operation of electrical energy networks. During the steady state study of an electrical network any one of the possible contingencies can have either no effect, or serious effect, or even fatal results for the network safety, depending on a given network operating state. In power system operation contingency analysis assists engineers to operate at a secured operating point where equipment are loaded within their safe limits and power is delivered to customers with acceptable quality standards. Real time implementation of power system analysis and security monitoring is still a challenging task for the operators.

In general the state of the system is determined on the basis of ability to meet the expected demand under all levels of contingencies. The objective of contingency analysis is to find voltage violations or line overloads under such contingencies and to initiate proper measures that are required to alleviate these violations. Exhaustive load flow calculations are involved in ascertaining these contingencies and determining the remedial actions. The necessity for such tool is increasingly critical due to the emerging complexity of power systems 51 that results from network expansions and the fact that the power systems are pushed to operate at their limits due to financial and environmental constraints.

Voltage stability is defined as the ability of a power system to maintain steadily acceptable bus voltage at each node under normal operating conditions, after load variation following a change in system configuration or when the system is subjected to contingencies like line outage or generator outage. Single or multiple contingencies cause voltage violations which are known as voltage contingencies. The line outages may lead to the most severe violations in line flow which necessitates the line over load alleviation of the network.

2 METHODS OF CONTINGENCY ANALYSIS

There are various methods used for contingency analysis purpose. Methods based on AC power flow calculations are considered to be deterministic methods which are accurate compared to DC power flow methods. In deterministic methods line outages are simulated by actual removal of lines instead of modeling. AC power flow methods are accurate but they are computationally expensive and excessively demanding of computational time. Because contingency analysis is the only tool for detecting possible overloading conditions requiring the study by the power system planner computational speed and ease of detection are paramount considerations. A brief description of these methods is given below:

2.1 DC load flow method of contingency analysis

This method is based on DC power flow equation to simulate single or multiple contingencies. These equations are N-1 in number, where N is the number of buses. In this method the line resistances are neglected, only real power flows are modeled ignoring the reactive power flows. This results in a linear model of the network to facilitate performing multiple contingency outages using the principle of super position.

2.2 Z-matrix method of contingency analysis

This method makes use of bus impedance matrix associated with both base case system and the system modified by either line removals or additions [22]. Z-matrix of a system can be obtained by inverting the bus admittance matrix or it can be constructed by using available algorithms. The fundamental approach to contingency analysis using z matrix method is to inject a fictitious current in to one of the buses associated with the element to be removed, of such value that the current flow through the element equals the base case flow; all the other bus currents are set equal to zero. In effect, this procedure creates throughout the system a current flow pattern that will change in the same manner as the current flow pattern in the AC load flow solution when the element in question is removed. This method is more accurate compared to DC load flow method and the results are comparable to those obtained using AC power flow.

2.3 Voltage stability index (l-index) computation:

The Voltage Collapse Proximity Indicator (VCPI) was introduced by Kessel and Glavitch [3] for a two-bus system model and was generalized for a multi node system using a hybrid model for the power system. This indicator utilizes the information obtained from a normal load flow solution. The method can be used to determine local indicators corresponding to each load bus. The indicator L varies in the range between 0 (no load of system) and 1 (voltage collapse) values close to one indicate proximity to power flow divergence. Based on the concept, various models are derived which allow the predicting of voltage instability or the proximity of a collapse under various contingencies such as loss of generators or lines as well as load variations. The advantage of the method lies in the simplicity, reliability and it can give a good indication about the critical power a system can maintain before collapse over the whole region and for all the cases studied. A local indicator j L for each node j can be calculated as explained below:

Consider a system where n be the total number of buses with 1,2,…,g be the generator buses, and g+1,…,g+s, be switchable VAR compensator (SVC) buses, g+s+1,…, n be the remaining (n-g-s) load buses. Using the load flow results, the L-index value, computed at load buses is given as

$$Lj = 1 - \sum_{i=1}^{i=g} Fji \times Vi \div Vj$$

The value of L-index lies between 0 and1. An L-index value less than 1 (unity) and close to 0 (zero) indicates an improved voltage stability margin. The values Fji are obtained from the Y-bus matrix given by ([FLG])

4 CASE STUDY

In this paper sample four bus system is considered for contingency analysis using load flow studies. The system is simulated using power world simulator and it is shown in figure 1.

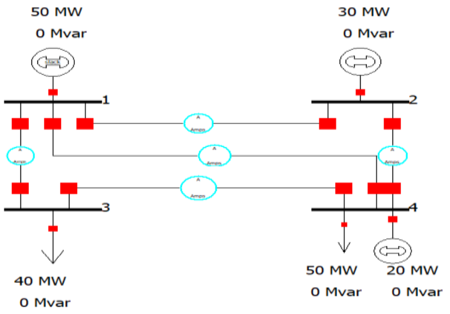


Fig 1: Sample system

System data for the simulation is given in Table 1 and Table 2

Table 1: Bus data

Bus No.	Type	V	Pg	Qg	Pd	Qd	Qmin	Qmax
1	slack	1	0.5	-	0	0	-0.2	1
2	PV	1.02	0.3	-	0	0	-0.2	1
3	PQ	1.05	0	0	0.4	0.4	0	0
4	PV	1.03	0.2	-	0.5	0	-0.2	1

Table 2: Line data

Branch No.	From Bus	To Bus	R	X
1	1	2	0.02	0.2
2	1	3	0.04	0.1
3	1	4	0.05	0.15
4	2	4	0.02	0.23
5	3	4	0.03	0.41

The above system is simulated for various load conditions using power world simulator. Also each line contingency is considred and power flow analysis is carried out to get volatge magnitude and angles at all four busses.

4.1 ANALYSIS USING ARTIFICIAL NEURAL NETWORK

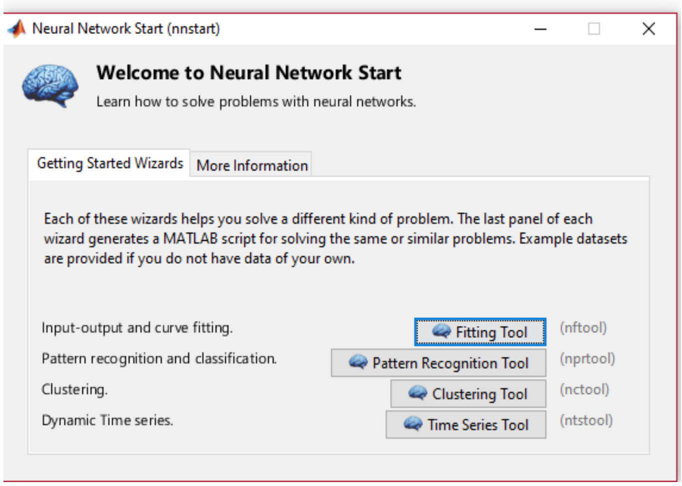
In recent years there has been a confluence of ideas and methodologies from several different disciplinary areas to give rise to an extremely interesting research area called artificial neural net research or connectionist net research. The concept of Artificial Neural Networks (ANN) is one of the greatest developments of this century. These networks resemble the functioning of human brain like intelligent guessing and pattern recognition. ANNs use large number of interconnected, concurrently operating elemental processors to process the information in a collective manner. Neurons are the basic building blocks and the input output relationship solely depends on the interconnection of the nodes and layers. Artificial neural networks are best suitable for nonlinear function approximation, estimation and prediction.

4.1.1 Data set Preparation:

As we are using ANN to perform the contineqency study, in this paper 60% to 120% load conditions are considred and for each load condition one normal condition and five contineqency conditions are considred and load flow analysis is carried out and corresponding volatges and angles at each busses are noted down. The matrix consisting of load condition in one column and contingency in second column which is of order 78X2 is taken as input to train ANN. And corresponding voltage magnitude and angles at all four busses which is of order 78X8 is considered as target to train ANN.

5 RESULTS AND DISCUSSIONS

The ANN is trained using ANN toolbox of MATLAB, the starting window of toolbox is shown in figure 2. The fitting tool app in this window is opened and data prepared in excel sheet is imported for training in window shown in figure 3. Once the data is imported the number of neurons are fixed and data for validation testing and training are fixed as shown in figure 4. The ANN is then trained using LavengergMarquardit algorithm. The correctness of ANN trained is assured by observing the regression value which should be near one and also MSE should be least. Onec the ANN is trained, corresponding Simulink diagram is generated and it is used further to perform contingency study for different load conditions and for outage of any line.



Neural Network Start (nnstart)

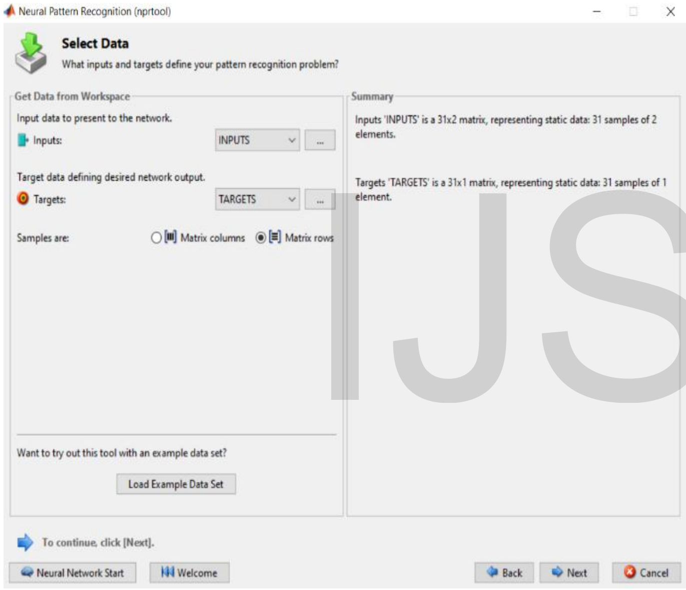
Welcome to Neural Network Start

Learn how to solve problems with neural networks.

Each of these wizards helps you solve a different kind of problem. The last panel of each wizard generates a MATLAB script for solving the same or similar problems. Example datasets are provided if you do not have data of your own.

Input-output and curve fitting.	Fitting Tool	(nftool)
Pattern recognition and classification.	Pattern Recognition Tool	(nprtool)
Clustering.	Clustering Tool	(nctool)
Dynamic Time series.	Time Series Tool	(ntstool)

Fig. 2: Start to Neural Network



Neural Pattern Recognition (nprtool)

Select Data

What inputs and targets define your pattern recognition problem?

Get Data from Workspace

Input data to present to the network.

Inputs: INPUTS

Target data defining desired network output.

Targets: TARGETS

Samples are: ○ Matrix columns ● Matrix rows

Summary

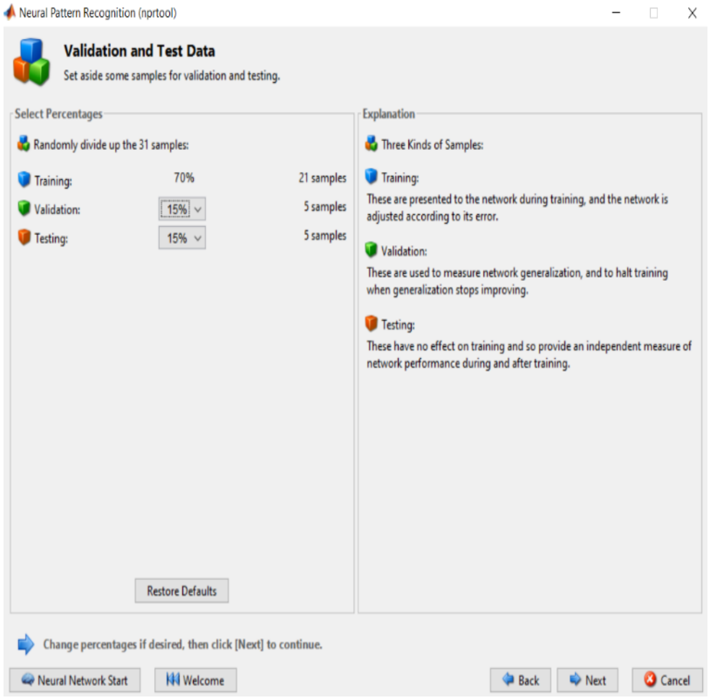
Inputs 'INPUTS' is a 31x2 matrix, representing static data: 31 samples of 2 elements.

Targets 'TARGETS' is a 31x1 matrix, representing static data: 31 samples of 1 element.

Want to try out this tool with an example data set?

To continue, click [Next].

Fig. 3: Importing the INPUT and TARGET variables



Neural Pattern Recognition (nprtool)

Validation and Test Data

Set aside some samples for validation and testing.

Select Percentages

Randomly divide up the 31 samples:

Training:	70%	21 samples
Validation:	15%	5 samples
Testing:	15%	5 samples

Explanation

Three Kinds of Samples:

Training:
These are presented to the network during training, and the network is adjusted according to its error.

Validation:
These are used to measure network generalization, and to halt training when generalization stops improving.

Testing:
These have no effect on training and so provide an independent measure of network performance during and after training.

Change percentages if desired, then click [Next] to continue.

Fig. 4: Validation and Test Data

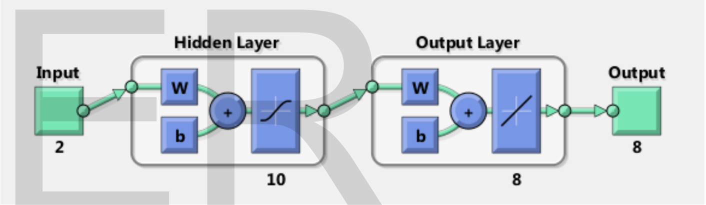


Fig. 5: Trained Neural Network

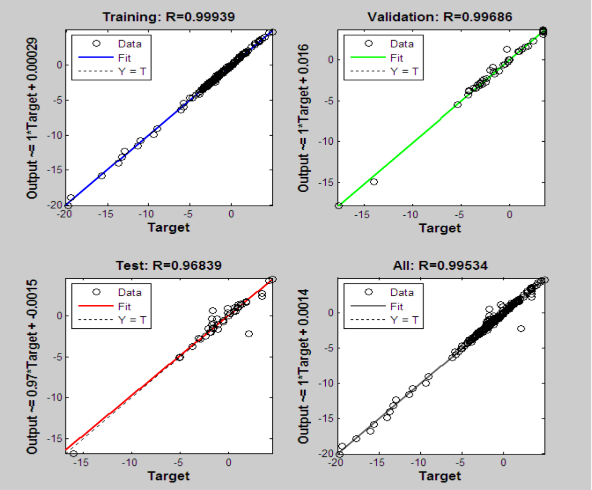


Fig. 6: Regression Plots

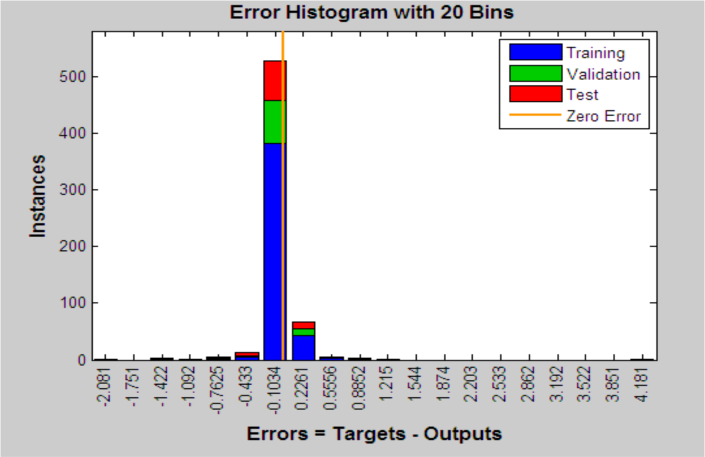


Fig. 7: Error histogram

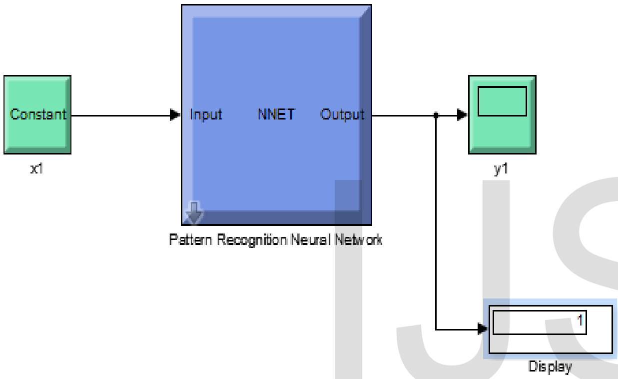


Fig. 8: Simulink diagram for Neural Network

6 CONCLUSION

The analysis of contingencies, particularly line outages is important to utilities in both operation and planning, if the potential outage of a line or generator would result in overload of another line, then the system is said to be vulnerable, a condition which should be quickly detected for possible corrective rescheduling actions in operation, or for system redesign in planning. In this paper a method of contingency analysis using neural network is proposed to estimate the post contingency state of the power system. The results obtained from the proposed method can be further used to perform contingency ranking so as to decide about most critical continigency.

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Appendix

Input set for training ANN

%load	Contingency number	%load	Contingency number
60	0	65	3
65	0	70	3
70	0	75	3
75	0	80	3
80	0	85	3
85	0	90	3
90	0	95	3
95	0	100	3
100	0	105	3
105	0	110	3
110	0	115	3
115	0	120	3
120	0	60	4
60	1	65	4
65	1	70	4
70	1	75	4
75	1	80	4
80	1	85	4
85	1	90	4
90	1	95	4
95	1	100	4
100	1	105	4
105	1	110	4
110	1	115	4
115	1	120	4
120	1	60	5
60	2	65	5
65	2	70	5
70	2	75	5
75	2	80	5
80	2	85	5
85	2	90	5
90	2	95	5

95	2	100	5
100	2	105	5
105	2	110	5
110	2	115	5
115	2	120	5
120	2		
60	3		

Target Set for training ANN

V1	δ 1	V2	δ2	V3	δ 3	V4	δ 4
1	0	1	1.796	0.9915	-1.442	1	-0.122
1	0	1	1.769	0.99	-1.693	1	-0.179
1	0	1	1.638	0.9897	-1.75	1	-0.461
1	0	1	1.507	0.9894	-1.808	1	-0.742
1	0	1	1.48	0.9879	-2.06	1	-0.8
1	0	1	1.349	0.9876	2.118	1	-1.082
1	0	1	1.217	0.9873	-2.176	1	-1.364
1	0	1	1.19	0.9858	-2.429	1	-1.422
1	0	1	1.058	0.9855	-2.487	1	-1.705
1	0	1	1.031	0.9839	-2.742	1	-1.763
1	0	1	0.899	0.9836	-2.8	1	-2.047
1	0	1	0.767	0.9833	-2.859	1	-2.331
1	0	1	0.739	0.9817	-3.114	1	-2.389
1	0	1	4.966	0.9924	-1.213	1	0.992
1	0	1	4.605	0.9921	-1.287	1	0.63
1	0	1	4.532	0.9906	-1.541	1	0.557
1	0	1	4.17	0.9903	-1.615	1	0.195
1	0	1	4.096	0.9887	-1.87	1	0.122
1	0	1	3.733	0.9884	-1.945	1	-0.241
1	0	1	3.37	0.9881	-2.02	1	-0.605
1	0	1	3.296	0.9865	-2.276	1	-0.679
1	0	1	2.931	0.9861	-2.351	1	-1.043
1	0	1	2.856	0.9845	-2.608	1	-1.118
1	0	1	2.491	0.9841	-2.683	1	-1.484
1	0	1	2.461	0.9825	-2.942	1	-1.559
1	0	1	2.049	0.9821	-3.018	1	-1.925
1	0	1	1.001	0.983	-9.016	1	-1.827
1	0	1	0.839	0.983	-9.364	1	-2.176
1	0	1	0.673	0.9785	-10.96	1	-2.532
1	0	1	0.509	0.9785	-11.31	1	-2.883
1	0	1	0.342	0.9734	-12.94	1	-3.242
1	0	1	0.178	0.9734	-13.29	1	-3.593
1	0	1	0.014	0.9734	-13.64	1	-3.945
1	0	1	-0.15	0.9734	-13.99	1	-4.298
1	0	1	-0.32	0.9677	-15.65	1	-4.661
1	0	1	-0.48	0.9677	-16.00	1	-5.016
1	0	1	-0.65	0.9614	-17.69	1	-5.382
1	0	1	-0.82	0.9544	-19.41	1	-5.751
1	0	1	-0.99	0.9544	-19.77	1	-6.107
1	0	1	1.715	0.9913	-1.478	1	-0.296
1	0	1	1.397	0.9907	-1.618	1	-0.978
1	0	1	1.332	0.9891	-1.886	1	-1.118
1	0	1	1.014	0.9884	-2.026	1	-1.801
1	0	1	0.948	0.9868	-2.295	1	-1.942
1	0	1	0.629	0.9861	-2.436	1	-2.627
1	0	1	0.308	0.9854	-2.577	1	-3.314
1	0	1	0.242	0.9837	-2.848	1	-3.457
1	0	1	-0.07	0.983	-2.99	1	-4.144
1	0	1	-0.14	0.9812	-3.263	1	-4.289
1	0	1	-0.46	0.9805	-3.404	1	-4.979
1	0	1	-0.53	0.9787	-3.679	1	-5.124
1	0	1	-0.86	0.9779	-3.821	1	-5.816
1	0	1	3.464	1	-1.657	1	-1.17
1	0	1	3.464	0.9902	-1.732	1	-1.535
1	0	1	3.464	0.9886	-1.987	1	-1.61
1	0	1	3.464	0.9882	-2.062	1	-1.976
1	0	1	3.464	0.9867	-2.318	1	-2.052
1	0	1	3.464	0.9863	-2.393	1	-2.418
1	0	1	3.464	0.9859	-2.468	1	-2.786
1	0	1	3.464	0.9843	-2.726	1	-2.862
1	0	1	3.464	0.9839	-2.802	1	-3.231
1	0	1	3.464	0.9823	-3.06	1	-3.308
1	0	1	3.464	0.9819	-3.136	1	-3.678
1	0	1	3.464	0.9803	-3.396	1	-3.755
1	0	1	3.464	0.9789	-3.473	1	-4.126
1	0	1	1.979	0.9874	-1.741	1	-0.271
1	0	1	1.818	0.6874	-1.741	1	-0.074
1	0	1	1.818	0.9852	-2.037	1	-0.074
1	0	1	1.657	0.9852	-2.036	1	-0.42
1	0	1	1.657	0.9829	-2.33	1	-0.419
1	0	1	1.496	0.9829	-2.332	1	-0.766
1	0	1	1.334	0.9829	-2.332	1	-1.113
1	0	1	1.334	0.9806	-2.631	1	-1.112
1	0	1	1.173	0.9806	-2.63	1	-1.46
1	0	1	1.01	0.9806	-2.63	1	-1.808
1	0	1	1.01	0.9783	-2.93	1	-1.808
1	0	1	1.848	0.9872	-2.93	1	-2.157
1	0	1	1.848	0.9759	-3.231	1	-2.156