Power Systems Contingency Analysis using Artificial Neural Networks

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Abstract

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.

Load flow analysis can be used as a crisp technique for contingency risk assessment. However performing at run time the necessary load flow analysis studies is a tedious and time consuming operation. An alternative solution is the off-line training and the run-time application of artificial neural networks.

This article aims at describing how artificial neural networks can be used to bypass the traditional load flow cycle, resulting in significantly faster computation times for online contingency analysis. A discussion over the efficiency of the proposed techniques is also included.

1. Introduction

Artificial Neural Networks (ANNs), have been successfully applied to a variety of problems, due to their abilities to approximate real-value, discrete-value and vector non-linear target functions [1]. ANNs have been used effectively during recent years in power system applications (see [10]. [11], [12]).

The application of ANNs to a system requires, as in other machine learning tools, the identification of salient system parameters capable to describe well the laws that characterise the mechanics of the system.

Traditional load flow algorithms apply iterative procedures to solve an electrical network computing system parameters like bus voltages and line flows.

A system contingency is defined as a disturbance that can occur in the network and can result in possible loss of parts of the network like buses, lines, transformers, or power units in any of the network areas.

Load flow analysis is an adequate means for studying the effect of a possible contingency on a given operating point of the network. It is often the case that experienced engineers, involved in operation of a given system, can guess effectively contingency without the support of numerical computations. This intuition of the operators is useful in supporting the initial selection of a list of possible contingencies, which then will be analysed using the described here technique.

Within this article a set of macroscopic system parameters are presented, capable of representing the overall characteristics of the system under a certain contingency. These parameters, in a normalized form, are subsequently used as input ANN parameters. The output layer of the network makes a classification for the contingency applied on any given operating point: “innocent”, “serious” and “fatal”. The cases where operating violations are observed are considered as “serious”, while the cases for which the load flow algorithm exhibits a diverging algorithmical solution, are considered as “fatal”.

Within the scope of this article, the network of the island of Crete, see Fig.1, has been considered suitable for experimentation, as a medium sized network, while for power flow network solutions the PCFLO power flow analysis toolkit has been used [6]. For ANN training and testing, DMSK (Data-Miner Software Kit 1.01) tools have been used.[4] All tests conducted were the results of 20-Fold Cross Validation tests, aiming at the maximal reduction of the statistical bias. The ANNs used, were

Proceedings of the 4th International Workshop on Computer Science and Information Technologies CSIT’2002
Patras, Greece, 2002

feed forward ANNs with one hidden layer and a variable number of hidden nodes.

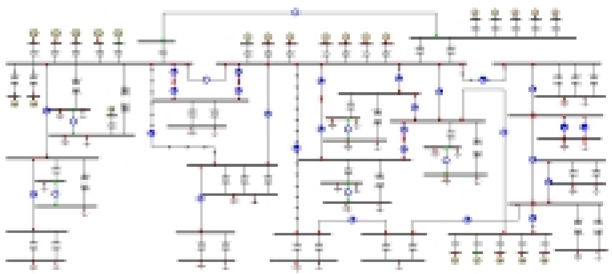

Figure 1. The electrical network of the island of Crete.

2. System Architecture

A suitable way of studying the effects of contingencies on an electrical network is through the definition of representative operating points, creation of a relevant data base, in which parameters relating to these operating points is stored as these have been measured directly through network snapshots. The creation of a data base containing network operating points is very important, as the network during its operation can be found in many different conditions depending on load, power generation and network connectivity factors. From this point of view the state of an electrical network becomes more interesting for study when operating under extreme or particular conditions. Bearing this in mind, we can conclude that if we created an operating points data base, by sampling the network at regular time intervals, then this would not be necessarily the most efficient process, as some critical network states, can be missed while, on the other hand, we would find ourselves with a database where "ordinary" operating points would be over-represented.

On the other hand, operating points' creation by simulation is an attractive solution to this problem. In our study, we select a maximum load base case and create a set of operating points by simulation, varying the load, generation and network connectivity parameters. The operating points produced are subsequently screened for voltage and current limit violations (see appendix). The violating cases are discarded, while the valid ones are stored in the operating points data base, as real world network snapshots.

Once a number of operating points is simulated, a list of contingencies to be studied upon is formed. Each contingency is applied on all operating points found in the database and then a power flow solution is attempted on the network. According to the results of the power flow solution the contingency applied of the specific operating point can be ranked as "innocent", "violating", or "diverging / serious". The pre-contingency operating point parameters, various operating point indices and metrics, the contingency and the power flow result are next stored in a table per contingency.

This contingency table constitutes a set of features and tuples that can be considered as suitable neural network input layer data elements if selected in any combination and after being statistically normalized. The power flow solution classifying any contingency for any operating point, is the output layer value of the neural network.

Neural network training is a computer intensive work that needs, however, to be done only once. As soon as the neural network is trained for a contingency, the predictions about the effects of a contingency on any operating point can easily be deduced. The efficiency of the predictions depends on various factors such as the quality and the quantity of the training features, the type, complexity and connectivity of the neural network.

3. Neural Network Input Feature Selection

A wide range of electrical network parameters can be used for describing the network state. Some of them can be the network load level expressed as a percentage of the maximal network load, the number of lines, the cumulative rating of all lines, the cumulative active load, active generation, reactive load, reactive generation, apparent power etc.

In recent bibliography there are references in more elaborate aggregates that yield better results when applied, such as the active apparent power margin index (expressed as the fraction of the flowing aggregate apparent power, over the aggregate MVA line transmission limits) and the voltage stability index. The voltage stability index is computed as "the sensitivities of the total reactive power generation to a reactive power consumption, known as 'reactive power dispatch coefficients' ". [3]

Neural networks can be trained with any number of input features. The neural network training process can selectively overweight the most salient features and underweight the least significant ones. However, the selection procedure is time consuming for the training of the neural network, while after the training is complete, it is not always obvious which of the input nodes are of greater importance. Further more, the least important input layer nodes may add noise to the neural network training process. Bearing this in mind, a pre-selection of the neural network input nodes is of great use. This can be achieved through the use of statistical methods.

The statistical methods that apply in the procedure of the selection of features are used in the classification theory. The classification of a set of training examples by two features in two classes is considered to be better when the sub-populations look different. In [4], the simplest test proposed is the test of separating two classes using just the means. A feature selection test from Means and Variances is also proposed:

$$se(A-B)=\sqrt{\frac{\mathrm{var}(A)}{n_1}+\frac{\mathrm{var}(B)}{n_2}}$$

and

$$\frac{|\,mean(A)-mean(B)\,|}{se(A-B)}>sig$$

where

A and *B* are of the same feature measured for the classes 1 and 2

n_1 and n_2 are the corresponding number of cases

sig is a significance level.

In [4] the following measure for filtering features separating two classes is also proposed:

$D_M = (M_1 - M_2)\,(C_1 + C_2)^{-1}\,(M_1 - M_2)^T$

where M_1 and M_2 are the vectors of feature means for class 1 and class 2, C_1^{-1} and C_2^{-1} are the inverse of the covariance matrix for class 1 and class 2 respectively.

The statistical feature selection formulae aggregates mentioned above, were applied to the electrical network of Crete for a set of seven different contingencies and 272 different simulated operating points.

For reasons of simplicity, a combination of bus and line losses only has been considered as a constituent element of a contingency under study.

The four most salient features found were the aggregate reactive power generation, the voltage stability index, the aggregate MVA power flow and the real power margin index. This set of selected features has been used for the training and testing of the neural networks subsequently built.

4. Cross Validations, Sensitivity analysis and the Quality index

N-fold cross validation is a widely used practice in the literature of neural networks. It consists of the execution of N independent tests aiming at benchmarking the predictive performance of a neural network, avoiding any sort of statistical bias. During a cross validation, the tuples of data are split at random at training and testing data at a certain percentage. The training data are used for training the neural network, while the remaining testing data are used for testing the predictive power of the neural network being built. Every time a validation is performed, the data are split at random once again to training and testing data and the neural network is trained again out of the training set of data. Thus, the statistical bias is minimized, while after a number of validations are executed the average predictive hit rate corresponds in great extend to the average real life behavior of the neural network being built. The number of cross validations executed for the tests conducted was twenty. A higher number of cross validations would add more overhead, while a smaller number of tests would add more bias to the results.

Sensitivity analysis refers to the execution of N-fold cross validations, mutating some of the conditions of the experiments conducted. Mutation may refer to the addition or subtraction of an additional training feature or the examination of the effects a change of the training / testing percentage set quota would have on the predictive behavior of a neural network.

The *quality index* is a qualitative measure of the classification power of the neural network. It is an index that has been calculated for all simulations and applies on the idea that within the three classes of contingency states, the major difference can be considered to occur between two possible categories of contingencies: “innocent” and “non-innocent” contingencies. In order to compute this “quality index” (*QA)* the following formula has been used:

$$QA=\frac{\sum_{i=1}^{3}a_{i,i}+0.5*\left(a_{1,2}+a_{2,1}+a_{2,3}+a_{3,2}\right)}{\sum_{i=1}^{3}\sum_{j=1}^{3}a_{i,j}}$$

where $a_{i,j}$ is the *I*-th element of the *j*-th column of the confusion matrix $A_{i,j}$. The confusion matrix $A_{i,j}$ is a matrix of frequencies. For each element of the matrix $a_{i,j}$ the *i* index refers to predicted values, while the *j* index refers to real values. The values range from one to three denoting the three possible contingency cases: one in case of non-convergence / potentially serious contingency, two in case of MVA and voltage violations and three in case of an innocent contingency.

5. Experiments conducted, results, conclusions and further discussion

A list of 20-fold cross validations has been conducted for the complete set of all proposed training features for feed forward neural networks of two, three, four and eight hidden nodes of an one layer hidden layer neural network. Tables [1] and [2] illustrate collectively the results of these experiments, while figure 2 refers to the quality index of Table [1]..

For all the experiments the MLPSE tool has been used [5], in combination with the *PCFLO* power flow solution package and the *DMSK (Data-Miner Software Kit 1.01)*. The 20-fold cross validation execution times were satisfactory for up to 4 hidden node neural network training validations, while for 8 hidden nodes, the training times were rather long. However, it is easily concluded from tables [1] and [2], that for neural networks with eight nodes, the predictive powers of the neural networks built improve considerably.

Another conclusion is that the efficiency of the neural networks built is related to the nature of the studied contingency. Contingencies that tend to steadily express certain behavior for most of the operating points, train neural networks with higher predictive rates. This is the case of contingency number three that in most of the cases is classified as an "innocent" contingency. This is not the case however, for the fourth contingency where the average prediction rate is low. In what concerns the training to testing quota variations from a 70% - 30% to 85% - 15%, the overall results seem to be rather not sensitive to this factor.
We believe that the predictive success rate of the neural networks used can further improve if more elaborate qualitatively and quantitatively electrical network aggregate indices are used. We also believe that if crucial localized network specific information is added results can be further enhanced.

	Contg1	Contg2	Contg3	Contg4	Contg5	Contg6	Contg7	Average
2 Nodes	66.95%	56.95%	94.88%	49.63%	58.41%	65.85%	50.98%	**63.38%**
2 Quality Index	78.17%	69.33%	97.44%	63.05%	73.66%	78.54%	65.37%	**75.08%**
3 Nodes	70.37%	59.15%	91.34%	47.44%	55.49%	70.61%	58.54%	**64.71%**
3 Quality Index	80.49%	71.28%	93.17%	61.83%	71.16%	80.67%	71.77%	**75.77%**
4 Nodes	71.83%	61.59%	96.59%	53.66%	63.78%	72.32%	59.15%	**68.42%**
4 Quality Index	82.01%	72.50%	98.29%	64.94%	77.99%	82.93%	71.77%	**78.63%**
8 Nodes	73.66%	61.71%	96.46%	51.95%	65.12%	76.22%	58.78%	**69.13%**
8 Quality Index	84.02%	73.11%	98.23%	65.24%	79.51%	85.43%	72.50%	**79.72%**
Average	**75.94%**	**65.70%**	**95.80%**	**57.22%**	**68.14%**	**76.57%**	**63.61%**	**71.85%**

Table 1. Neural Network predictions for all features, 20-fold cross validations at 70% - 30% training – testing data set split quotas.

	Contg1	Contg2	Contg3	Contg4	Contg5	Contg6	Contg7	Average
2 Nodes	65.91%	55.36%	95.61%	49.33%	56.34%	66.28%	55.98%	**63.54%**
2 Quality Index	78.08%	67.98%	97.80%	62.59%	72.32%	78.45%	70.06%	**75.33%**
3 Nodes	68.54%	59.76%	95.37%	49.94%	60.91%	70.49%	56.46%	**65.92%**
3 Quality Index	79.36%	71.77%	97.68%	62.68%	76.34%	80.55%	70.09%	**76.92%**
4 Nodes	69.39%	59.63%	96.22%	52.20%	60.73%	71.89%	59.45%	**67.07%**
4 Quality Index	80.27%	71.65%	98.11%	64.42%	75.64%	82.77%	72.20%	**77.87%**
8 Nodes	73.78%	58.90%	96.16%	53.90%	66.95%	76.83%	62.62%	**69.88%**
8 Quality Index	83.20%	71.07%	98.08%	65.43%	80.79%	85.58%	74.30%	**79.78%**
Average	**74.82%**	**64.52%**	**96.88%**	**57.56%**	**68.75%**	**76.61%**	**65.15%**	**72.04%**

Table 2. Neural Network predictions for all features, 20-fold cross validations at 85% - 15% training – testing data set split quotas.

6. Conclusion

In this paper an innovative technique for performing contingency analysis of power systems using artificial neural networks has been proposed. This technique is involves a tedious training phase, where a set of neural networks is created, corresponding to a given set of possible contingencies. The resulting set of ANNs demonstrate satisfactory predictive power in classifying the contingencies correctly at run time. The run time performance of the system is very good in terms of computational time and recourses requirements.
Seven ANNs have been trained for predicting the severity of contingencies for the network of the island of Crete, the testing set performance of these ANNs was in the range of 57% to 96%, this performance did not seem to be affected by the split between the training and testing cases, as for both a 70-30 and a 85-15 split the results were similar, while sensitivity analysis in terms of the ANN architecture demonstrated that the number of hidden nodes seem to have a serious effect on the performance of the network, suggesting use of more complex ANNs.
The promising results of this study suggest application of similar techniques in other areas of security assessment of power systems and other industrial processes.

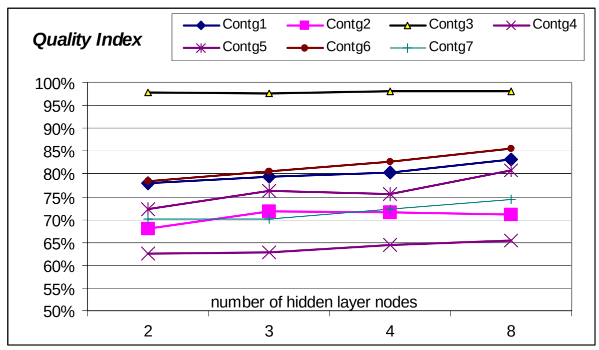

Figure 2. The quality index vs number of hidden layer nodes for the ANNs performance in 70-30 split of training and testing data sets

Acknowledgments

The research reported here is partially funded by GSRT and the Public Power Corporation of Greece under the YPER program of research - project "Contingency Analysis of Large Electrical Networks".

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Appendix

I. Line Overload Index:

$$LOI = \sum_{i=1}^{NL} \left(MVALine - MVALineLimit\right) \cdot MVALineLimit$$

where:
MVALine = The apparent power in MVA
MVALineLimit = The apparent power Limit in MVA
NL = Number of Lines

The proposed *LOI* index aims at avoiding the masking effect related problems weighting the contribution of each contingent violation of MVA transfer limits according to the importance of the line where the violation occurs.

II. A composite Voltage profile index

An Index to count any Major Violations occurring at any bus.

$$MA_{VVI} = \sum_i VB$$

where
MA_{VVI} = Major Voltage Violations Index
VB = Buses where Major Voltage Violations occur (i.e. for which Voltage
Magnitude per unit divergence in absolute value terms is greater than 10%,
regardless of the Voltage Bus Base).
i = Index covering all system buses.

A second Index to count minor violations is proposed as follows:

$$MI_{VVI} = \frac{\sum_{i=1}^{NB} abs(VMBus_i - VMLim}{NVVB}$$

where
MI_{VVI} = Minor Voltage Violations Index
$VMBus_i$ = Voltage i-Bus Magnitude expressed in per unit terms
VMLim = The upper or lower per unit limit for over voltages and under voltages respectively. (A 5% limit is proposed, configuring the upper limit at 105% p.u. and the lower limit at 95% respectively for each bus)
NB = Number of Buses
NVVB = Number of voltage violating buses (within a 5% proposed limit).

On MI_{VVI} a state estimator hypothesis in built in MLPSE comparing the index with a global percentage safety limit. Thus for a 5% proposed limit, any operation point bearing an MI_{VVI} index greater or equal to 1.05 is regarded as violating and consequently "unsafe".