

# Application of Back-Propagation Artificial Neural Network for Voltage Security Assessment

Shubhranshu Kumar Tiwary<sup>1</sup>, Jagadish Pal<sup>2</sup>, Chandan Kumar Chanda<sup>3</sup>

<sup>1</sup>Research Fellow, Electrical Engineering Department, Indian Institute of Engineering Science and Technology, Shibpur

<sup>2,3</sup>Professor, Electrical Engineering Department, Indian Institute of Engineering Science and Technology, Shibpur  
<sup>1</sup>sktiwary1986[at]gmail.com, <sup>3</sup>ckc\_mathes[at]yahoo.com

**Abstract:** A power system is always subjected to internal and external complications that may lead to instability in the system. The social and economic consequences of a major power supply interruption are so great that every effort must be made to reduce the impact of such a disturbance. The process of determining the steadiness of the system following the disturbances is known as security assessment. In particular, steady state voltage security assessment is a process to evaluate the static security of the power system following a disturbance. It is done considering the loading conditions in respect of voltage profile at the buses. Each bus is operated on a range of voltage magnitude, beyond which the voltage profile of the whole network is perturbed. In this paper voltage security assessment with help of Artificial Neural Network has been reported. Load flow studies are an integral part of security assessment of a power system but they are generally computationally intensive task and time consuming. As an alternative and less computationally intensive method, the artificial neural network is used in this paper to detect a set of critical conditions of a 2 machine 5 bus system.

**Keywords:** Power System Static Security, MW Security Assessment, Artificial Neural Network

## 1. Introduction

A power system is continuously subjected to different types of disturbances and can never be assumed to be secure. The process of determining whether it remains in the secure state or insecure state is known as power system security assessment. There are two outlooks of the security assessment problem: Static security assessment and dynamic security assessment.

Static security assessment evaluates the post contingent steady state of the system neglecting the transient behavior and any time dependent variations due to changes in the load-generation conditions.

Dynamic security assessment evaluates the time dependent shift of a power system from the pre-contingent state to the post-contingent state due to small and large disturbances. Small disturbances affect the dynamic stability of the power system while the large disturbances affect the transient stability.

This paper focuses on the voltage security assessment aspect of static security assessment of a power system.

The basic tool for Steady State Security Analysis is the Load flow. It is impractical to study all the possibilities of circuit outages by full ac load flow techniques due to time constraints in on-line environment. For voltage security analysis, we use Fast Decoupled Load Flow in on-line since it is a one-shot method of solution, it is very fast and more or less accurate for some systems where VAR problems are not that much severe. In off-line condition, Newton Raphson Load Flow (NRLF) may be used for both MW and Voltage security assessment.

In off-line or on-line studies, the methods for assessing security using NRLF or other load flows are not efficient,

they are generally tedious, time consuming and computationally intensive. An alternative approach may be the application of Artificial Neural Network for security assessment of power system.

In machine-learning and cognitive science, artificial neural networks (ANNs) are a family of models inspired by biological neural networks (the central nervous systems of animals, in particular the brain) and are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. Artificial neural networks are generally presented as systems of interconnected "neurons" which exchange messages between each other. The connections have numeric weights that can be tuned based on experience, making neural nets adaptive to inputs and capable of learning.

In particular, the multilayered neural network with error back propagation training algorithm is used to test the validity of the artificial neural network approach in determining the steady state voltage security assessment of the power system. While using this alternative approach, various parameters in the multilayered neural network such as the number of hidden neurons and the number of hidden layers are modified so as to minimize the error in the prediction of critical cases.

## 2. Static Security Assessment

One of the most important requirements for the normal operation of a power system is the nearly strict synchronism in the rotational speed of the many largely interconnected generating units. The consequence of any successive loss of synchronism among major systems or subsystems can prove to be disastrous.

In the operation of electrical power systems disturbances are always present, either of external or internal origin. External

disturbance may be caused due to storms, lightning strikes, earthquakes, etc. Internal disturbances originate in the system itself like loss of generation, outages of line, random load variations. These disturbances may lead to a shift in the operating state and initiate small oscillations of the system variables such as frequency. If the oscillations are damped out, the system stays in the stable state and pull through the following transients. If the system is unstable, one or more machines may lose synchronism with the rest of the power system.

Power system security assessment is the investigation performed to determine whether, and to what extent, a power system is reasonably safe from serious hindrance to its operation. The assessment involves evaluation of available data to approximate the security level of the system in its present state or some near future state.

To assess voltage security of power system, contingency analysis is carried out as a routine activity in a modern control center. Branch MW flow and bus voltage magnitude are of prime importance for such studies. Violation of MW limit of a line and/or bus voltage limit will cause insecurity to the system. In on-line environment, contingency analysis is performed by running approximate load flow method i.e., DC load flow method for MW security assessment and 1P-1Q load flow method for voltage security assessment. Contingency ranking is done by calculating a scalar index called Performance Index (PI). Ranking list is obtained by arranging PI values in descending order. The higher PI values correspond to harmful contingency cases. A few of them starting from the topmost of the list are selected for further full ac analysis because these are harmful for secured operation of the system. Contingency evaluation is done by running accurate load flow method for the selected harmful cases. Newton Raphson load flow or FDLF is preferred for both MW and voltage security analysis.

Contingency analysis is performed by creating various scenarios of a system. It may be tripping of a line, a transformer, a breaker, a generator or even a bus bar. It may be variation of bulk amount of active and reactive load or generation.

Contingency analysis is a software application run in an energy management system to give the operator an indication of what might happen to the power system in the event of an unplanned (unscheduled) equipment outage. That is, the contingency analysis application allows the operator to ask what if questions such as: *What will be the state of the system if a 400 kV major transmission line trips?* The answer to this question might be that the system power flows and voltages will just read and remain within acceptable limits, or the answer might be that severe overloads and/or under-voltages will occur.

An overload itself can damage the transmission and the generating equipment if it is severe enough and exists for a long period. It may cause uncontrollable cascade tripping resulting in shut down of large part of power system. The use of contingency analysis application in an energy management system is predicated upon the idea that when forewarned, the operator can take some action before or

after the event that will help the system to avoid problems. As such its economic justification come from the electric utility desire to avoid overloads that might directly damage equipment, or might cause the system to lose a number of components due to relay action.

### 3. The Artificial Neural Network Approach

The artificial neural network can be used as an alternative approach to voltage security assessment to overcome the difficulties faced using the conventional methods. In this alternative approach we use a large amount of load flow data collected by performing off-line load flow analysis which includes active and reactive load and generation variations. The data is used to train the selected neural network. When trained the neural network will be able to classify the conditions whether the system is normal or under/over loaded.

There are various classes of artificial neural network that can be used to solve different types of problems. Here a multilayer neural network with error back propagation has been used.

#### 1) Multilayer Neural Network with Error Back propagation

The multilayer neural network with error back propagation is the most commonly used neural network. It has been successfully used for solving a variety of problems in the past in power system security. Here it is used to classify the power system operating states which ultimately determines the security. The network consists of an input layer, one or more hidden layers of neurons and an output layer. The input signal is propagated in the network from the input layer to the hidden layer to the output layer. This network is generally trained in a supervised manner.

##### a) Error Back propagation algorithm

The error back propagation consists of two passes through different layers of the network; namely forward pass and backward pass. In the forward pass, the input vector is applied to the nodes and propagates through the network layer by layer, and ultimately a set of outputs is produced as the actual response of the network. During the forward pass the weight vector does not change.

In the backward pass, the error signal is propagated backward through the network against the synaptic weights. The weighting vector are adjusted so as to match the actual output of the network to the desired output.

##### b) Rate of learning

Sometimes a learning rate coefficient is used to train the network. The learning rate affects the rate of change of synaptic weights in the network. The smaller the learning rate, the smaller will be the changes in the synaptic weights of the network from one iteration to the other, and it will take much longer to train the network. However, if we take a very large learning rate the network may give oscillatory results.

### c) Momentum term

Large learning rates often lead to oscillation of weight changes and learning never completes, or the model converges to a solution that is not optimum. One way to allow faster learning without oscillation is to make the weight change a function of the previous weight change to provide a smoothing effect. The momentum factor determines the proportion of the last weight change that is added into the new weight change.

### 2) Optimum Structure

Within the structure of the multilayered neural network, the various parameters (number of hidden layers, neurons and activation function) can be modified to achieve different prediction results. As there are no exact criteria for the determination of the best combination of all the parameters, they are varied in a somewhat trial and error manner to obtain the optimum structure that will give rise to the minimum error in the prediction.

## 4. Implementation

The proposed artificial neural network approach for the power system voltage security assessment is described in the following steps:

### Step-1: Generating the training data

A standard 5 bus power system has been used for the study. The NRLF program was run successively several times, by varying some specific parameters every time. The voltage magnitude on each bus was computed by varying the active and reactive power of load and generation. Each of them was (individually) varied from 50 % to 150 %. Then the corresponding line flows are accumulated in a documented format. Out of the total data calculated, 75% of the data are set aside for training and the remaining 25% data for testing the network.

### Step-2: Selection of the neural network inputs

The choice of inputs is an extremely crucial factor in the successful use of the artificial neural network to predict the security state condition of the system. In this study, the voltage magnitude on each bus is taken as inputs to the network and a certain percentage of the threshold of bus voltage magnitude (range 0.95 p.u. to 1.05 p.u.). The state of Power System is classified as insecure (0) or secure (1). The detailed process is explained as follows.

In FDLF program, various input data are changed one by one and the load flows are run for each case. The standard input data for a 5-bus system is given below:

**Table 1:** Bus data of standard 5 bus system

Bus No.	Bus Voltage Magnitude (initial)	Generation		Load	
		MW	MVAR	MW	MVAR
1	1.06	0.0	0.0	0.0	0.0
2	1.0	40.00	30.00	20.00	10.00
3	1.0	0.0	0.0	45.00	15.00
4	1.0	0.0	0.0	40.00	5.0
5	1.0	0.0	0.0	60.00	10.00

All the data collected from the load flow studies are tabulated into two excel sheets: one for training and one for testing.

### Step-3: Training the neural network

With the choice of appropriate inputs, the network is trained with the data generated until the error reaches a minimum. The trained network with the highest accuracy is then saved for testing the remaining data.

### Step-4: Adjusting the neural network parameters

In order to optimize the performance of the neural network in the present study, different parameters of the network are changed according to our necessity. The parameters changed are:

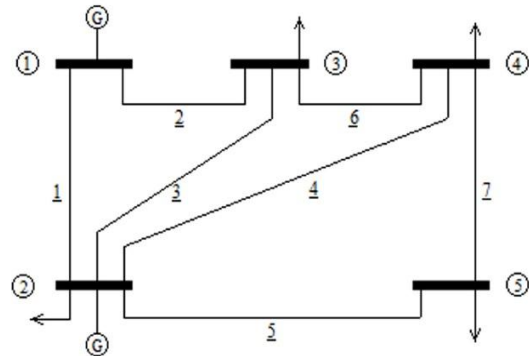
- Number of input nodes
- Number of hidden neurons
- Number of hidden layers
- Activation function
- Network Architecture

### Step-5: Testing the trained network

After successfully training the network and obtaining the desired result the network is tested with the testing data to verify the accuracy of the network. If testing gives accurate results then it may be concluded that, the network has successfully converged.

## 5. Case Studies

According to the steps mentioned in the previous section the neural network is applied to a standard 5 bus power system shown in Figure 1.



**Figure 1:** Line diagram of a standard 5 bus system

Around 400 datasets are collected by varying the active and reactive power of load and generation and running FDLF program, out of which 300 datasets are used for training and the remaining 100 datasets are used for testing the network.

The optimal results were obtained using a single hidden layer, with 3 hidden neurons and the logistic activation function. The confusion matrix of the tested data is shown in Figure 2. The results on the 5 bus system are found to be quite accurate. The accuracy during training was found to be 99.7% and the accuracy during testing was found to be 99.0%.

**Confusion Matrix**

Output Class	0	40 40.0%	0 0.0%	100% 0.0%
	1	1 1.0%	59 59.0%	98.3% 1.7%
		97.6% 2.4%	100% 0.0%	99.0% 1.0%
		0	1	
		Target Class		

**Figure 2:** Confusion matrix while testing the network

## 6. Discussion

This paper presents a new direct method for voltage security assessment of a multi-bus power system. Artificial neural network is used to determine the security state of power system for a 5 bus system. With the neural network approach, the system security can be determined with much higher accuracy in a very short time, demonstrating the benefits of using the proposed approach and potential of the artificial neural network.

The network architecture of the artificial neural network in the optimal prediction of the states of the system will be different for different power system. The network architecture must be varied according to the complexity of the power system in context. It is something that has to be found by trial and error method, until the best performance has been achieved.

It is inferred that with the increase in the complexity of the power system, the need for the amount of the training data also increases. It is seen that the best results have been obtained using a logistic activation function. During the training, encouraging results have been obtained with a hidden layer of three neurons with an accuracy of more than 99%. When we increase the number of neurons in hidden layer the accuracy decreases gradually.

The results obtained were quite accurate and encouraging. The accuracy during testing was 99%. With the results obtained it can be said that the artificial neural network does provide a good alternative approach for MW security assessment.

However, in this context a few points must be noted.

- The accuracy of the artificial neural network obtained here may be due to the fact that it is applied to a small system. The accuracy may vary for larger system.
- There is no specific neural network structure that can give accurate results for all power systems. Studies need to be done to determine the optimum network structure for different power systems. Different parameters must be varied to obtain the best results and the training data must also cover a wide range. The multilayered network with error back propagation algorithm is generally a

useful network that is able to solve a multitude of problems including the prediction of the MW security.

Power industries may be reluctant to use ANN in on-line in their systems. As long as the artificial neural network is not used in on-line, further developments will still be only on a theoretical basis and results obtained are conceptual. Only if the power firms are willing to try out the new technology, the artificial neural network can be further tested and refined. A lot of work still needs to be done because of the inherent uncertainties of the artificial neural network.

However, the actual realization of the neural network approach is another point to be considered. The physical model of building the artificial neural network needs to be implemented as analog, digital or hybrid hardware. To develop an artificial neural system chip that is usable is an non-trivial task, has so far proved to be costly.

In addition, the uncertainty in determining the best combination of the various neural network parameters shows that it is more of an art than science to obtain the best performance. Experience of the operator can play an important role in determining the best neural network structure to use.

## 7. Conclusion

The determination of the voltage security of a power system is not an easy task. It is a complex process which consumes a lot of time. The conventional methods have their own drawbacks especially of being very time consuming and computationally intensive.

In conclusion, the artificial neural network approach is found to be able to give quite accurate results in predicting voltage security but it needs some improvements to be actually used online in practical power systems. The reason being that the risk involved in introducing new technology is too high for most power sectors and the reservations itself ironically limit the process of developing the artificial neural network approach further.

## References

- [1] D. Srinivasan, C. S. Chang, A. C. Liew and K. C. Leong. "Power System Security Assessment and Enhancement using Artificial Neural Network", International Conference on Energy Management and Power Delivery, 1998, Vol 2, IEEE
- [2] Qin Zhou, Jennifer Davidson and A. A. Fouad. "Application of Artificial Neural Networks in Power System Security and Vulnerability Assessment" IEEE PES 1993 Winter Meeting, Paper No. 93.
- [3] D.J. Sobajic and Y-H Pao. "Artificial Neural-Net Based Dynamic Security Assessment for Electric Power Systems", IEEE Transactions on Power Systems, Vol 4, No.1 pp 220-4, Feb 1989.
- [4] M. Aggourne, M.A. El-Sharkawi, D.C. Park, M.J. Damborg and R.J. Marks II. "Preliminary results on using artificial neural networks for security assessment" IEEE Transactions on Power Systems, Vol 6, No2 May 1991.

- [5] Pao and D.J Sobajic. "Combined use of unsupervised and supervised learning for dynamic security assessment" IEEE Proc. of PICA '91 pp 278-284, Baltimore, MD, May 1991.
- [6] Dipti Srinivasan, C. S. Chang, M. K. Sim, "PowerSystem Security Assessment using Artificial NeuralNetwork", Journal of the Institution of Engineers, Singapore, Vol. 36, No. 6, 1996, pp. 67-70.
- [7] M.E Aggoune, L. E. Atlas, D. A. Cohn, M. J. Damborg, M. A. El-Sharkawi, and R. J. Marks. "Artificial Neural Network for Power System Static Security Assessment", IEEE International Symposium on Circuits and Systems, 1989, Vol 1, pp. 490-494
- [8] I. S. Saeh and A. Khairuddin. "Static Security Assessment Using Artificial Neural Network", 2nd IEEE International Conference on Power and Energy (PECon 08), December 1-3, 2008, pp. 1172 - 1178

## Author Profile

**Shubhranshu Kumar Tiwary** is currently working towards his Ph.D. in the Department of Electrical Engineering at Indian Institute of Engineering Science and Technology, Shibpur. He completed his B. Tech in 2011 from WBUT and his M.E. in 2013 from BESU, Shibpur.

**Jagadish Pal** obtained his B.E. and M.E. in Electrical Engineering from Jadavpur University, Kolkata in the year 1977 and 1980 respectively. He did his Ph.D. from Bengal Engineering and Science University, Shibpur, Howrah in the year 2002. Presently he is working as a professor in the department of Electrical Engineering at Indian Institute of Engineering Science and Technology (formerly Bengal Engineering and Science University), Shibpur, Howrah. He has three years of industrial and thirty-one years of teaching experience. He has published two papers in national journals and five papers in national and international conferences.

**Chandan Kumar Chanda** is working as a Professor in the Department of Electrical Engineering, IEST, Shibpur, India. He obtained his B.E. degree from R.E. College Durgapur, and M.Tech. in Electrical Engineering from IIT Kharagpur, in the year 1983 and 1989 respectively. He obtained a Ph.D. degree from the Department of Electrical Engineering, B.E. College (DU), Shibpur, India with a specialization in Power Systems. Dr. C. K. Chanda has over 31 years of teaching and research experience in the diverse field of Power Systems Engineering and 4 years of experience in the industry. His areas of interest include Smart Grid, Resiliency, Stability, and Renewable Energy. He is a recipient of Tata Rao Gold Medal. He is actively involved in various research projects funded by Centrally Funded Organizations like DST, UGC. He has published 150 research articles in reputed National/International journals and conferences including 42 research papers in SCI-indexed journals. He is a member of the Editorial Board and Guest Editor of numerous reputed Journals. He has authored and co-authored four (4) books in reputed publishing houses like Mc Graw Hill, PHI etc. He has contributed five (5) book chapters in International Proceedings. Ten (10) research scholars have got their Ph. D. degree under the supervision of Dr. Chanda. Currently, nine (9) students are pursuing research under him. More than twenty - five (25) Ph. D. thesis has been evaluated by him. He is a senior member of IEEE.