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TRAINING EFFECTS ON NEURAL NETWORK METHODS FOR VOLTAGE STABILITY INDEX COMPUTATION

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Abstract- Voltage stability assessment plays a key role in operations of power systems. Neural network based assessment techniques are gaining a lot of attention in this area. In this work, we presents the effects of training parameters on assessment of voltage stability index based on the real field data .The stress on the bus is analyzed on the basis of real and reactive power, and the changes in the index based on contingencies in the system is presented. The work is focused on radial distribution power systems and is based on Kerala grid, India.

Index terms- *voltage stability, L-index, neural network*

I. INTRODUCTION

A stable power system can be said as the backbone of today's industrial and scientific developments in every sector .Apart from the generating stations, the body of the power systems can be said as the transmission system that is operated through substation. The correction methods taken by the transmission systems for reactive power, incorporating capacitor banks plays a great role in preventing voltage collapse. The primary objective of this work is to compute voltage stability index which acts as a pointer to the system operator on the stress on each major bus on his station.

Much work has been done in the field of voltage stability indices [1-3].The accuracy of stability assessment is complex due to the number of variables needed to consider. Due to the high non-linearity in the calculations and the computational complexity involved, methods based on Neural Networks plays an important role in this area. The self-learning capability of Neural networks and the easiness in which can be modeled to solve real world problems makes it an exact choice for voltage stability studies. Fast computing powers developed recently makes neural networks much effortless.

Reactive power management is one of the key steps in Preventing voltage collapse[4-5]. Voltage stability analysis gives the system operator ,enough decision making assistance for this management by knowing the stress on the major buses .The present work focuses on the dynamic modeling of voltage stability index[6] for the nonlinear mapping and aims at transmission subsystems. Lots of work was done in the area of voltage stability analysis with artificial neural network [7-10].These works differ in the type of neural network employed, methods of training and application background. Also works [11-12] are done in the analysis of radial distribution feeders. But most of the papers published relied on the load patterns generated by software programs .This kind of approach cannot fully show the characteristic nature of a power system .Hence we used real field data obtained from the subsystem. This gives more realistic results on the system. In the present work we followed the work done by Debbie and Anna age [13].In that work they worked on long-term voltage stability margin using ANN. The work done by the authors of [6, 14] also helped to shape our approach on this problem. But all this works did not gave much importance on the effects of the training parameters on the voltage stability assessed. In this work we focus on the training parameters like volumes of data used in training, testing and validation of neural network as well as the number of hidden neurons.

In the following sections we describe a brief introduction to the neural networks and architecture involved, the methodology of the work and the work background and the results obtained.

II. ANN AND THE ARCHITECTURE USED

Lots of literature were published regarding the neural networks and its basics[15]. Artificial neural networks imitates the biological neural network in its structure and performs well in the problems of pattern classification and function approximation The network is made of data processing units or neurons which are interconnected by adjustable weights. The network learns to adjust its weight by certain algorithm. In the present work we employed a 3 layer neural network with back propagation [6, 13] which is trained by LM algorithm. It has an input layer, hidden layer and an output layer. Here we used sigmoid function in the hidden layer and linear function in the output layer. The structure used in the present work is shown in Fig1.

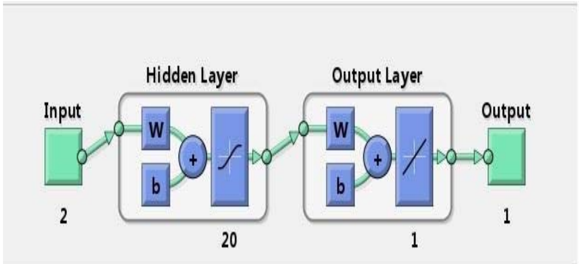

Fig 1: Structure of Multilayer Feed Forward network

The major objective is to train the neural network to predict the stability index from the self- learning capability of the network. In this work we used the active power and reactive power as the input variables and the bus voltage as the output. The stability index is calculated from the predicted output bus voltage by using the standard formulae for the 2 bus system [16].This was derived from the Improved Distribution load flow technique [17].

$$L= 4(V_0V_L-V_L^2)/ V_0^2 \qquad (1)$$

V_0=No load voltage, V_L =load voltage and L=stability index. An L=0 indicates fully stable condition and L=1 means unstable. The target output bus voltage calculates the stability index and hence it is indirectly the output of the neural network.

III .BACKGROUND AND METHODOLOGY OF THE WORK

The approach we followed can be summed up in the following steps. The work background was a 110 KV substation in which stress of the main bus is observed by computing its stability index. The bus had two input feedings of 110 KV, with two output 33kv feeders, and five 11 KV outgoing feeders. The load patterns of 6 months were collected for the computation of the stability index. We find the stability index of this major bus on which the feeders are connected.

1. From the real field data, classify the data according to the contingencies. From this a data base consisting of the input vectors (P and Q) and output variable (V) is made.

2. Created the neural network structure using Matlab. We used MSE (mean square error) and R-correlation value as the performance indicators of the neural network.

3. Divide the input data into 3 classes of datasets according to the volume of training, validation and testing.

Class A-90% Training,5% validation,5% Testing
ClassB-80% Training,10% validation,10% Testing
ClassC-60% Training,30% validation,10% Testing

4. Choose the optimum number of hidden neurons by a number of trials by varying the number of hidden neurons and observing the performance. Choose the number of hidden neurons which offer best performance in terms of MSE and R.

5. Train, validate and test the input patterns .check the performance of the network .compare the predicted index and the index derived from the equation 1.find the best combination of training parameters.

IV.RESULTS AND DISCUSSION

Number of hidden neurons: Increasing the number of hidden neurons increases the complexity and time taken for running the program. Finding the optimum number of hidden neurons required several trials. The number of hidden neurons was found in an optimum range of 20.This was found by trying 10,15,20,25 neurons in the hidden layer. The results here are for 11 KV contingency with class B.

Table 1
Comparison of Number of neurons with MSE

Number of hidden neurons	MSE(Mean square Error)
10	$2.6739e^{-0}$
15	$1.4724e^{-0}$
20	$1.0149e^{-0}$

We are presenting the results on load patterns analyzed on 11kv contingency only the best class of data was found be class A. class A takes less epochs or reaches fastly the optimum combination of weights to reach the best MSE point. In the 11 KV contingency load patterns we studied class A takes 4 epochs to reach minimum MSE while others take nearly 16 epochs. It means that large volume of data influence the performance. The Fig 2 and Fig 3 give the comparison of class A and class B performance. Class C performance is almost same as class B in the number of epochs which is not shown.

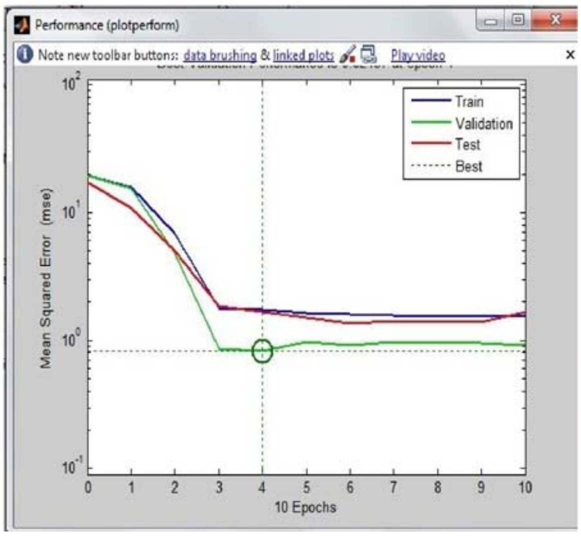

Fig 2: class A performance-11kv contingency

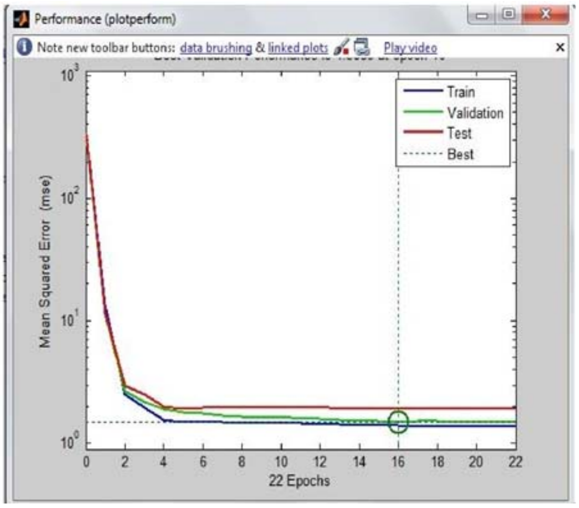

Fig 3: class B performance-11 KV contingency

The actual bus voltage and predicted bus voltage are also presented in Fig 4 .The prediction error can be minimized by adding more input variables, example phase angle, voltage etc.

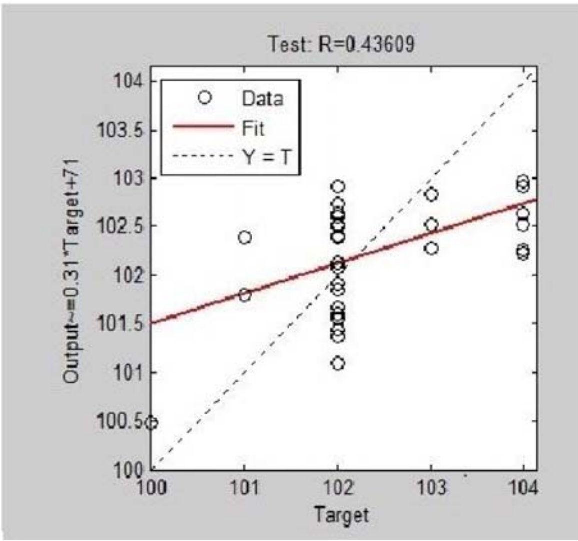

Fig 4: comparison of predicted and target bus voltage

We also present in Table 2 the MSE and R values for the 11 KV contingency case. A low value of MSE is desirable as well as a value closer to 1 is desirable for R.

Table 2
Class A –performance parameters

Parameter	Training	Validation	Testing
MSE	$1.562e^{-1}$	$9.87e^{-1}$	$1.57e^{-1}$
R	$3.546e^{-1}$	$4.83e^{-1}$	$4.227e^{-1}$

We are also presenting the stability index derived from the neural network as well as the actual L index from the equation (1).The results shows that the target L-index and actual L-index values are almost similar. A sample input data set and its corresponding results are given below in Table 3. According to the results obtained, a higher volume of training data or incorporating large load patterns results in better calculation of stability index and it also shows the self- learning capability of neural network, from the previous load patterns

Table 3:
Predicted index and L index

Active power	Reactive power	L-index	Predicted L-Index
-8	1	0.36	0.2482
-4	0	0.38876	0.2482
-6	-2	0.38876	0.2469
-4	-1	0.38876	0.2665

V. CONCLUSIONS AND OBSERVATIONS

The work presented the neural network computation of stability index and the effects of training. The results show that choice of training parameters affects the computation of the stability index. According to the results, a higher volume of training data or incorporating large load patterns results in better calculation of stability index. The studies shows that a better online stability monitoring system can be installed in transmission centers with a neural network computational program that can help the station operator control the amount of reactive power and other corrective measures for better voltage conditions and regulation of stress on major buses. The work has to be modified by extending the number of contingency situations and observe the tendency and ranges of indexes according to the contingency In the future the effects of other advanced networks like radial basis networks and different training algorithms has to be tested.

REFERENCES

[1] Kessel P, Glavitch H. Estimating the voltage stability of power systems .IEEE Trans. on Power Delivery, 1986, 1 (3): 346-354.

[2] “Voltage Stability Assessment, Procedures and Guides-Special Publication”, IEEE/PES Power System Stability Subcommittee special Publication 1998.

[3] P.Kessel and H. Glavitsch, "Estimating the Voltage Stability evaluation indices (APE and MAPE) were implemented to of a Power System," IEEE, Trans. on Power Delivery, Vol. PWRD- 1, No. 3, PP. 346-354, July 1986.

[4] Carolina M. Affonso, Luiz C. P. da Silva, Flávio G. M. Lima, and Secundino Soares,” MW and MVar Management on Supply and Demand Side for Meeting Voltage Stability Margin Criteria”,IEEE transactions on power systems, vol. 19, no. 3, august 2004.

[5] M. Bahadornejad and G. Ledwich,” on-line voltage collapse prediction considering composite load and on-load tap changer”, Australasian Universities Power Engineering Conference (AUPEC 2004) ,26-29 September 2004, Brisbane, Australia.

[6] Xiaoqing HAN, Zhijing ZHENG,Nannan TIAN,” Voltage Stability Assessment Based on BP NeuralNetwork”, 978-1-4244- 2487-0/09/, 2009 IEEE.

[7] EI-Keib, X Ma, “Application of Artificial Neural Network in VoltageStability Assessment”, IEEE Trans. Power System, Vol. 10, no 4, pp.1890-1896, Nov 1995.

[8] J. A. Momoh and L. G. Dias,” Investigation of Artificial Neural Networks for Voltage Stability Assessment”, 0-7803-2559-1/95 ,1995 IEEE.

[9] S.N. Singh a,*, 1, L. Srivastava b, J. Sharma c,” Fast voltage contingency screening and ranking using cascade neural network”,Elsevier, Electric Power Systems Research 53 (2000) 197– 205.

[10] G. Cell,Loddo, F. Piloand M. Usai,” Voltage Collapse Prediction with Locally Recurrent Neural Networks”, 0-7803-7519- X/02/ ,2002 IEEE.

[11] Mohamed M. Hamada, Mohamed A. A. Wahab, Nasser G. A. Hemdan,” artificial neural network modeling technique for voltage stability assessment of radial distribution systems”, Al-Minia University, Egypt.

[12] Antonino Augugliaro, Luigi Dusonchet, Stefano Mangione,” Voltage Collapse Proximity Indicators for RadialDistribution Networks”, 9the International conference on Electrical power quality and utilization, Barcelona, 2007.

[13] Debbie Q. Zhou, U. D. Annakkage,andAthula D. Rajapakse, “Online Monitoring of Voltage Stability Margin Using an Artificial Neural Network”, IEEE transactions on power systems, vol. 25, no. 3, august 2010.

[14] Worawat Nakawiro, and István Erlich, Online Voltage Stability Monitoring using Artificial Neural Network”, DRPT2008 6-9 April 2008 Nanjing China.

[15] A Caudill, M., and C. Butler, Understanding Neural Networks: Computer Explorations, Vols. 1 and 2, Cambridge, MA: The MIT Press, 1992.

[16] O.P. Rahi, Amit Kr Yadav, Hasmat Malik, Abdul Azeemb, Bhupesh,” Jun Zhan Power System Voltage Stability Assessment through ArtificialNeural Network”, Elsevier, International Conference on Communication Technology and System Design 2011.

[17] T.K.Abdul Rehman and G. B. Jasmon, “A new technique for voltage stability analysis in a power system and improved load flow algorithm for distribution network,” International Conference on EMPD, vol .2, pp. 714-719, Nov 1995.

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