International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249 – 8958, Volume-1, Issue-3, February 2012

Comparison between learning mechanism and pattern presentation techniques in voltage stability assessment

Ali Akbar Motie Birjandi, Saeed rahimi gholami

Abstract— ***In this paper we compare learning mechanism and pattern presentation techniques in voltage stability assessment. In this way we use multilayer perceptron and classifiers models for assessing power system voltage stability margin in unstable point. In this paper we consider voltage magnitudes and phase angles as input and voltage stability margin as target of ANNs. Simulation was carrying out on IEEE-14 bus test system and numerical results show that minimum rule in combination gives better results rather than other models. Also be specified that use learning mechanism lead to better results than apply pattern presentation techniques.***

Index Terms*—*Artificial Neural Network , Combination of Classifiers ,Voltage Stability ,Voltage Stability Margin

I. INTRODUCTION

Voltage stability is the power system ability to maintain acceptable voltages at all system buses under normal conditions and after exposure to disorders. The system is close to voltage instability when a disorder, increase in loader change in system condition lead to Non-reversible and progressive decrease in the voltage profile. Voltage stability can be divided into Large and small disturbance voltage stability.

Large disturbance voltage stability:

This type of voltage stability is referred to system ability to voltage control following the occurrence of major disturbances such as system errors, loss of load or loss of production.

Determining this kind of stability involves study dynamic performance of the system using non-linear simulation in the time domain.

Small disturbance voltage stability:

This type of voltage stability is referred to system ability to voltage control following the occurrence of small disturbances such as gradual changes in load. Determining this kind of stability involves study steady-state methods which use linearization of system dynamical equations around the operating point. Distance to voltage instability can be measured based on quantities such as the load level, real power passes and reactive power reserves. Different tasks has been taken to predict voltage stability and point close to voltage collapse based on the conventional and traditional methods such as active power- voltage curve, reactive power – voltage curve, indexes based on the sensitivity, energy, the voltage stability margin. Due to need repetitive calculations and long time have been excluded. For examples:

- Methods based on the reduced Jacobin matrix have problems in split parts.

- Dynamic models for generators and loads in power systems are complex and time consuming in the other hand analysis of the obtained models require high computing and software package will be expensive in this paper we use multi-layer perceptron and classifier neural network models to estimate the voltage stability margin. CHOSE the neural network inputs are very important. Neural network Inputs may be different.

- Bus voltage and impedance of the load and the reactive power consumption [9]

- Active and reactive power of load bus [5]

- Active and reactive power of load busses and voltage magnitude of load and generator busses [6]

- Active and reactive power of load busses and voltage magnitude of load and generator busses, reactive power reserve and pulse Changers position [7]

In this paper we use voltage magnitude and voltage angle of the load busses as input to neural networks.

Comparing different combinations of neural networks in terms of response time, frequency, performance and regression result that minimum model in combination lead to the best answer than other models .It also is clear that the mechanisms of learning leads to better results than applying the techniques of pattern displaying

II. PROCEDURE FOR PAPER SUBMISSION

Voltage stability margin:

Voltage stability margin is one of the most important indicators of the power system voltage stability. And it is important to know how far current system operating point to voltage instability is? This index can be evaluated in two areas of energy and power. Since the index can be more understood and more tangible in power area, in this paper we describe the voltage stability margin in this area [8]

Voltage stability margin definition:

Voltage stability margin is the distance from operating point to voltage collapse point based on MW. To determine the voltage stability margin which is the maximum loading level,

Saeed Rahimi, Shaheed Rajaee Teacher Training/ Electrotechniques/ Tehran, Iran, +986637226133/ +989359287714., (e-mail: srahimi5118@yahoo.com).

Ali Akbar Motie Birjandi, Shaheed Rajaee Teacher Training, University/ Electrotechniques, Tehran, Iran, +982122970027/ +989126200817., (e-mail: motiebirjandi@yahoo.com).

we used power full continuation power flow algorithm. In this algorithm active and reactive power of load busses and active power of the generator busses will slowly increase from operating point to the voltage collapse point. The algorithm use predictive and corrective steps for determining the voltage claps point.
Direction of increase active and reactive power at load and generator busses:

Voltage stability margin depends on how active and reactive power of load and generator busses be increased. Which typically can increase un same as follows:

$$Pg = Pgo + \lambda Pgd$$

$$Pl = Plo + \lambda Pld$$

$$Ql = Qlo + \lambda Qld$$

Which Pgo, Plo and Qgo are the operation point values and Pgd, Pld and Qld are directions of changing load and generator busses power [1].

Formulating voltage stability margin:

If in p-v curve for load busses represent operating point power with Po and load bus power with $P\max$, definite voltage stability margin as fallow:

$$P\mathrm{margin} = P\max - Po$$

Neural network used for voltage stability margin assessment:

In this paper we use multilayer perception and the combined category of neural network model to estimate the voltage stability margin that the structure of them is shown in figures (1) and (2).

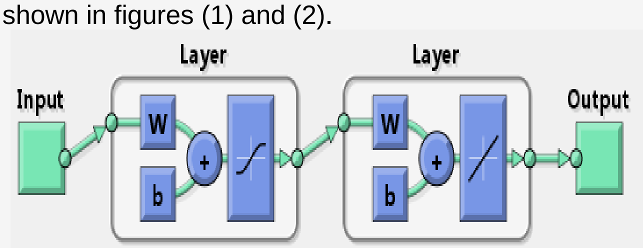

Fig 1.multy layer perception neural network stricter

This one with 25 neurons in the hidden layer and the learning rates 0.7.

Combined machines:
Combined machines are composed of two parts, basic classifier and combiner. Output of basic classifier is input of combiner. The combined output is output of the system.

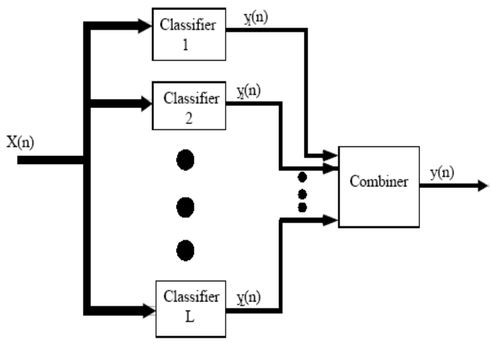

Fig2.combined machines

Machines used in this paper have 3 classifiers which number of hidden layer neurons, the maximum number of iterations, learning rate and momentum coefficient is shown in Table 1
Static combination strategies:
In this type of composition, the input vectors not applied to combiner and just the output of classifiers applied to the combiner.

Static combiners are two kinds
*1:nontrainabl:*The combination of neural networks or other machine learning is not used, but the same rules as minimum, maximum, sum, multiplication, and ... Is used.
2: trainable: The neural network is used which output of classifiers used as input to this type of combiners. [10, 11]
In this paper we have been fitted from the non trainable static combination strategy.

Different learning mechanisms:

A. - The use of different learning algorithms

B - Using a learning algorithm with different complexity

C - Use of a learning algorithm with different parameters

The different display patterns:

A - Use a different set of features or different set of laws

B – Use decimation techniques

Even when we have a set of features available, for train different classifiers can generate different sets of features eliminating different parts of the existing feature set [12].
In this paper we Use decimation techniques.
C - Divide the set of features in a system using a network

III. NEURAL NETWORK SIMULATIONS

Generate neural network training data:

with random changes of active and reactive power of load buses in the size range 50 to 150% of nominal and random change of the generator bus voltage in the range 0.8 to 1.2 (in per unit), and continuation power fellow in PSAT software, voltage stability margin for different loading levels is calculated.800 data were produced which750 of them used in training and the rest of them have used testing neural network.
Neural network training:
Magnitude and angle of the load busses voltage as input and voltage stability as well as the output of neural networks are considered. A total of 22 features were selected as neural network input. Using analysis of the major components number of inputs was reduced to 18.All the training data have been divided into three categories. Then train the first classifier with data 1 to 250, the second classifier with data 250 to 500Finally, the third classifier with data 500 to 750.

Neural network performance indicator:

To evaluate the performance of neural networks we have used mean square error (MSE).

$$F = MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2$$

Where, N is the number of training samples, t is the desired output of neural network and "a" as output.

Simulation results with different neural networks:

Using data produced we have educated the multi-layer perceptron and combined neural networks. We have been fitted from the no trainable static combination strategy. The average, maximum and minimum is used in combination. Then for learning mechanisms and techniques for the pattern recognition, we compare each of the combined models of response time, number of iterations, the performance and regression. Table 2, shows the results of the comparison.

IV. CONCLUSION

Conclusion:

Due to the ability of neural networks in solving non-linear problems, can be benefited estimation of the power system voltage stability. In this paper we have used of voltage stability margin as an indicator. using data generated we have trained the multi-layer perceptron and combined neural networks .by comparing the response time, number of iteration, performance and regression tells us, the minimum model in combination give the best answer to the other models. Also It is clear that using learning mechanisms leads to better results than applying pattern representation techniques.

REFERENCES

[1] Debbie.Q.Zhou,U.D.Annakkage,AthulaD.Rajjapakse *"onloine voltage stability monitoring of voltage stability margin using an Artifical Neural Network"*.IEEE Transaction on powersystems,vol 25,No.3,august 2010

[2] Gao,Marison G, Kudur P." Toward tht Development of a systemstic approach for voltage stability assessment of Larg-scale power systems". IEEE Trans power Syst 1996; 11(3):1314-23

[3] Lof PA, Smed T, Anderson G, Hill DI. *" Fast calculation of a voltage stability index"*. IEEE Trans power Syst 1992;2:54-64.

[4] P.Kundur, *Power system stability and control*. Newyork: Mc Graw-Hill Education,1994.

[5] P.J.Abrao, A.P.Aves da silva and A.C.Zambroni desouza,"Rule extraction from artificial neural networks for voltage security analysis",in proc.2002 int.Joint conf. Neural networks(AJCNN'02),May 12-17,2002,vol.3,pp.2126-2131

[6] S.Kamalasadan,A.K.Srivastavaand D.Thukaram, *"Novel algorithm for online voltage stability assessment basedon feed forward neural network"*,in proc.IEEE power Eng.soc.General meeting,Jun.18-22,2006.

[7] T.M.L. Assis, AR.Nunes, and D.M.Falco, *" Mid and Long-term voltage stability assessment using neural network and quasi-steady-state simulation"*,in proc. Power Engineering,2007 Large Engineering systems conf., oct. 10-12, pp. 213-217.

[8] T.Van Custem and C.Vournas, *"voltage stability of Electric power systems"*, Norwell, MA:Kluwer, 1998.

[9] V.R.Dinavahi and S.C.Srivastava, *"Artifical Neural Network based voltage stability margin prediction*", inproc.IEEE power Eng.Soc.summer Meeting, jul. 2001, vol.2, pp. 1275-1280

[10] Ledesma, P. andJulio Usaol. 2005. "*Doubly Fed Induction Generator Model for Transient Stability Analysis*".IEEE TRANSACTIONS ON ENERGY CONVERSION. VOL. 20, NO. 2:388-397.

[11] Haykin, Simon.1999. Neural Networks: "*A Comprehensive Foundation*." 2nd edition, Prentice-Hall.

[12] Windeatt T, Ghaderi R.1998. "*Dynamic Weighting Factors for Decision Combining*", *Proc. of IEE Int. Conf. On Data Fusion*, Great Malvern, UK: 123-130.

Table1. MLP and committee machines parameters

Neural network	No of hidden layer neuron	Max number of epoch	Learning rate	Momentum coefficient	Learning mechanism or pattern representation techniques
MLP	25	25	0.7	0.03	
Average model in combiner	NN1:25 NN2: 28 NN3: 32	25 25 25	0.7 0.7 0.7	0.03 0.03 0.03	A learning algorithm with different complexity
	NN1:25 NN2:25 NN3:25	15 20 25	0.5 0.7 0.9	0.01 0.03 0.05	learning algorithm with different parameters
	NN1:23 NN2:25 NN3:28	15 10 25	0.5 0.8 0.7	0.01 0.03 0.05	decimation techniques
Maximum model in combiner	NN1:20 NN2:25 NN2:30	25 25 25	0.7 0.7 0.7	0.03 0.03 0.03	A learning algorithm with different complexity
	NN1:25 NN2:25 NN2:25	15 25 35	0.5 0.8 0.9	0.02 0.04 0.05	learning algorithm with different parameters
	NN1:20 NN2:25 NN2:30	15 15 35	0.5 0.8 0.9	0.01 0.03 0.05	decimation techniques
Minimum model in combiner	NN1:25 NN2:30 NN2:35	25 25 25	0.7 0.7 0.7	0.03 0.03 0.03	A learning algorithm with different complexity
	NN1:25 NN2:25 NN2:25	15 25 35	0.5 0.8 0.9	0.01 0.03 0.04	learning algorithm with different parameters
	NN1:25 NN2:28 NN2:32	15 20 25	0.7 0.8 0.9	0.01 0.01 0.01	decimation techniques

Table 2.compare different NN structures

Neural network	Response time	No of iterations	Error performance	Regressions	Learning mechanism or pattern representation techniques
MLP	4	22	0.0226	0.994	
Average model in combiner	4	11	Negligible	0.997	A learning algorithm with different complexity
	6	10	Negligible	0.993	learning algorithm with different parameters
	4	13	Negligible	0.995	decimation techniques
Maximum model in combiner	4	19	Negligible	0.996	A learning algorithm with different complexity
	4	12	Negligible	0.9721	learning algorithm with different parameters
	5	25	Negligible	0.993	decimation techniques
Minimum model in combiner	5	16	Negligible	0.9988	A learning algorithm with different complexity
	4	21	Negligible	0.999	learning algorithm with different parameters
	5	26	Negligible	0.996	decimation techniques