POWER SYSTEM DYNAMIC STABILITY ASSESSMENT USING FUZZY ARTMAP NEURAL NETWORK

SHAHRAM JAVADI

AZAD UNIVERSITY (Central Tehran Branch) & Moshanir Power Electric Company

IRAN
E-mail:
shahram_javadi@hotmail.com

MEHDI EHSAN

SHARIF UNIVERSITY OF TECHNOLOGY

IRAN
E-mail:
ehsan@ee.sharif.ac.ir

NASSER SADATI

SHARIF UNIVERSITY OF TECHNOLOGY

IRAN
E-mail:
sadati@ee.sharif.ac.ir

Abstract: This paper presents the application of Fuzzy ARTMAP neural network for evaluating on-line power system dynamic stability.
Using the matrix transformation of the S-matrix method, the absolute value of the most critical eigenvalue in Z-plane has been regarded as dynamic stability index of power system.
For evaluation of dynamic stability indices, a typical power system is tested and the results are compared with those obtained from classical multi-layer Perceptron. For on-line training, the Fuzzy ARTMAP network is found to be a better choice than the other neural networks. Also it is shown that the Fuzzy ARTMAP network has low sensitivity to the number of data set selection, which is used for training, and to the number of input bits.

Keywords: Power Systems, Dynamic Stability, Fuzzy ARTMAP Neural Network

1. Introduction

An important task in power system operation is to decide whether the system is currently operating safely, critically or unsafely.

Requirements for dynamic stability techniques consist of both the computational efficiency and high accuracy. Eigenvalue analysis is one of the conventional methods in dealing with the dynamic stability problems. In this paper the stability is evaluated by calculating the eigenvalue of the system matrix in the linearized dynamic equation. However, many of analytical methods used for determination of these eigenvalues such as QR method [1] and modal analysis [2] and some other methods are discussed in [3], [4].

These methods are very time consuming and difficult. More recently the application of neural network has developed in many of engineering problems. One of these problems is determination of critical eigenvalue in a power system done by back propagation method [5] or KOHONEN neural network classifier [6].

In this paper, a different approach is proposed for dynamic stability assessment. This approach is based on Fuzzy ARTMAP network. Because of self-organized characteristic of these networks, they can be used online in power systems for predicting stability indices. In [3] ARTMAP Network is used to evaluate the stability of power system, but it only states if power system is stable or not. It doesn't have any idea about stability indices.

This paper not only states the situation of power system from stability aspects but also computes stability margin of power system. In Section 2 the dynamic model of a power system is used and also the assessment of dynamic stability in power systems is introduced. Moreover it introduces the dynamic stability indices as a critical eigenvalue in dynamic model. Section 3 introduces a brief description of Fuzzy ARTMAP network at a level that is necessary to understand the main results of this paper. The experiments are discussed and the results are presented in section 4. Finally, the conclusions are drawn in section 5.

2. Dynamic Stability Assessment

The normal dynamic operation of a power system requires that all eigenvalues of a system to be in the left side of imaginary axis.

In a definite condition of loadflow, any power system has one critical eigenvalue, which is defined as the fastest eigenvalue that crosses imaginary axis in maximum load and maximum generation condition.

Using the S-matrix method [6], most critical eigenvalue in S-plane is regarded as maximum absolute value of eigenvalues in Z-plane.

Considering a power system under small disturbances, the linearized system state equation can be written as:

$$\dot{x} = A_s x \tag{1}$$

Where,
x: State variable vector
A_s: system matrix
Now, by assuming

$$x = [\Delta\delta, \Delta\omega, \Delta e'_q, \Delta V_A, \Delta E_{FD}, \Delta V_F]$$

We have:

$$A_s = \begin{bmatrix} 0 & 377 & 0 & 0 & 0 & 0 \\ -\frac{K_1}{M} & -\frac{D}{M} & -\frac{K_2}{M} & 0 & 0 & 0 \\ -\frac{K_4}{T_{d0}} & 0 & -\frac{1}{K_3T_{d0}} & 0 & \frac{1}{T_{d0}} & 0 \\ -\frac{K_AK_5}{T_A} & 0 & -\frac{K_AK_6}{T_A} & -\frac{1}{T_A} & 0 & -\frac{K_A}{T_A} \\ 0 & 0 & 0 & -\frac{1}{T_A} & -\frac{K_E}{T_E} & 0 \\ 0 & 0 & 0 & -\frac{K_F}{T_FT_E} & -\frac{K_EK_F}{T_ET_F} & -\frac{1}{T_F} \end{bmatrix} \quad (2)$$

The S-matrix method employs the transformation of the left half-plane into the unit circle i.e. transforming system matrix A_s into the following matrix:

$$A_z = (A_s + hI)(A_s - hI)^{-1} \quad (3)$$

Where,
A_z: transformed system matrix
I: unit matrix
h: positive real number

Equation (3) indicates a mapping transformation from S-plane to Z-plane as shown in figure 1, where the difference between the stable region in S-plane and in Z-plane is given in hatched area. Figure 1(a) denotes the stable region in S-plane while figure 1(b) illustrates the same one in Z-plane. The advantage of Z-plane is that the system stability depends upon the existence of eigenvalue within the unit circle. As a result, power system dynamics is evaluated by the absolute value of most critical eigenvalue of matrix A_z.

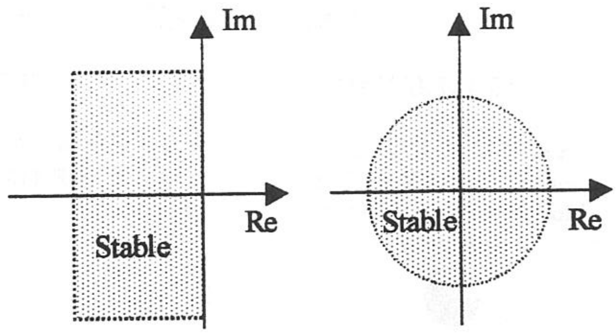
In the S-matrix method, the power system dynamic stability can be judged by the absolute value of the most critical eigenvalue such as

$$\mu = |\lambda_z^M| \quad (4)$$

Where λ_z^M is the most critical eigenvalue of matrix A_z. Therefore we have:

$$\begin{cases} \mu < 1 & \text{Stable} \\ \mu = 1 & \text{Critical Stable} \\ \mu > 1 & \text{Unstable} \end{cases} \quad (5)$$

Since the method makes use of mapping of the eigenvalue from S-plane to Z-plane, the most critical eigenvalue is the one with the largest absolute value in Z-plane. Now, the power system dynamic stability can be judged by examining if the eigenvalue with the largest absolute value exist within the unit circle as shown in figure (1):



(a) S-plane (b) Z-plane

Fig 1. Stable Region of Eigenvalues in s-plane and z-plane

3. The Fuzzy ARTMAP network

Fuzzy ARTMAP is a network with an incremental supervised learning algorithm, which combines fuzzy logic and adaptive resonance theory (ART) for recognition of pattern categories and multidimensional maps in response to input vectors presented in an arbitrary order. It realizes a new minimax learning rule, which jointly minimizes the predictive error and maximizes code compression, and therefore generalization [4].

A match tracking process that increases the ART vigilance parameter achieves this by the minimum amount needed to correct a predictive error. The Fuzzy ARTMAP neural network is composed of two Fuzzy ART modules, namely Fuzzy ART_a and Fuzzy ART_b, which are shown in figure (2).

After network is trained and clusters are created, then it is placed in parallel with power system to evaluate stability indices as shown in figure (3). The Fuzzy ARTMAP in prediction mode is shown in figure (4).

The interaction mediated by the map field F^{ab} may be operationally characterized as follows:

a) ART_a and ART_b

The inputs to ART_a and ART_b are in the complement code form:
For ART_a, $I=A=(a,a^c)$;
For ART_b, $I=B=(b,b^c)$;
For ART_a, let $x^a=\{x_1^a,\ldots,x_{2Ma}^a\}$ denotes the F_1^a output vector , $y^a=\{y_1^a,\ldots,y_{Na}^a\}$ denotes the F_2^a output vector, and $w_j^a=\{w_{j1}^a,\ldots,w_{j2Ma}^a\}$ denotes the jth ART_a weight Vector. Also for ART_b, let $x^b=\{x_1^b,\ldots,x_{2Mb}^b\}$ denotes the F_1^b output vector, $y^b=\{y_1^b,\ldots,y_{Nb}^b\}$ denotes the F_2^b output vector, and $w_k^b=\{w_{k1}^b,\ldots,w_{k2Mb}^b\}$ denotes the kth ART_b weight vector. For the map field, let $x^{ab}=\{x_1^{ab},\ldots,x_{Nb}^{ab}\}$ denotes the F^{ab} output vector and $w_j^{ab}=\{w_{j1}^{ab},\ldots,w_{jNb}^{ab}\}$ denotes the weight vector from the jth F_2^a note to F^{ab}.

b) Map Field Action

The map field F^{ab} is activated whenever one of the ART_a or ART_b categories is active. If node J of F_2^a is chosen, then its weight w_j^{ab} activate F^{ab}. If node K of F_2^b is chosen, then the node K in F^{ab} is activated by 1-to-1 pathways between F_2^b and F^{ab}. If both ART_a and ART_b are activated, then F^{ab} becomes active only if ART_a predicts the same category as ART_b via the weight w_j^{ab}.

The F^{ab} output vector x^{ab} obeys the following:

$$X^{ab} = \begin{cases} y^b \wedge W_J^{ab} & \text{if the Jth } F_2^a \text{ node is activated and } F_2^b \text{ is active} \\ W_J^{ab} & \text{if the Jth } F_2^a \text{ node is activated and } F_2^b \text{ is inactive} \\ y^b & \text{if } F_2^a \text{ is inactive and } F_2^b \text{ is active} \\ 0 & \text{if } F_2^a \text{ is inactive and } F_2^b \text{ is inactive} \end{cases} \quad (6)$$

By (6), $x^{ab} = 0$ if the prediction w_J^{ab} is disconfirmed by y^b. Such a mismatch event triggers an ART_a search for a better category.

c) Match tracking

At the beginning of each input presentation to the ART_a, vigilance parameter ρ_a equals a baseline vigilance ρ_{a0}. The map field vigilance parameter is ρ_{ab}. If

$$|x^{ab}| < \rho_{ab} |y^b| , \quad (7)$$

Then ρ_a is increased until it is slightly larger than $|A \wedge w_J^a| \cdot |A|^{-1}$, where A is the input to F_1^a in complement coding form. And

$$|x^a| = |A \wedge w_J^a| < \rho_a |A|, \quad (8)$$

Where J is the index of the active F_2^a node. When this occurs, ART_a search leads either to activation of another F_2^a node J with:

$$|x^a| = |A \wedge w_J^a| \geq \rho_a |A| \quad (9)$$

and

$$|x^a| = |y^b \wedge w_J^{ab}| \geq \rho_a |y^b| \quad (10)$$

Or, if no such node exists, to the shutdown of F_2^a for the remainder of the input presentation.

d) Map Field Learning

Learning rules determine how the map field weights w_{jk}^{ab} change through time. This can be done as follows: Weights w_{jk}^{ab} in $F_2^a \rightarrow F^{ab}$ paths initially satisfy:
$W_{jk}^{ab}(0) = 1$

During resonance with the ART_a category J active, w_J^{ab} approaches the map field vector x^{ab}. With fast learning, once J learns to predict the ART_b category K, that association is permanent, i.e., $w_{jk}^{ab} = 1$ for all time.

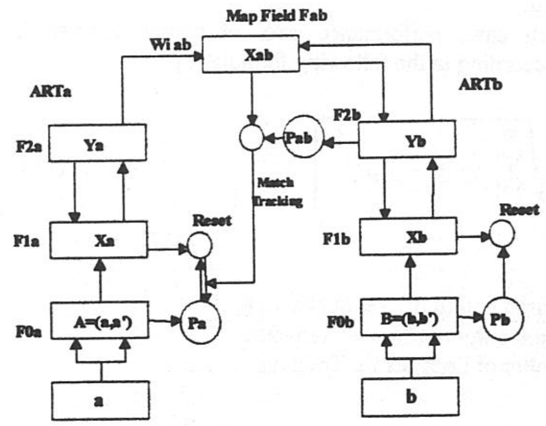


Fig.2. A typical Fuzzy ARTMAP architecture

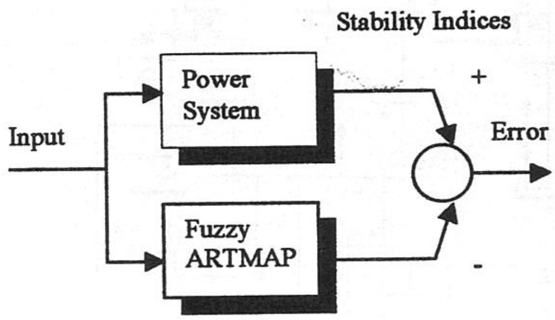


Fig.3. On-Line Training

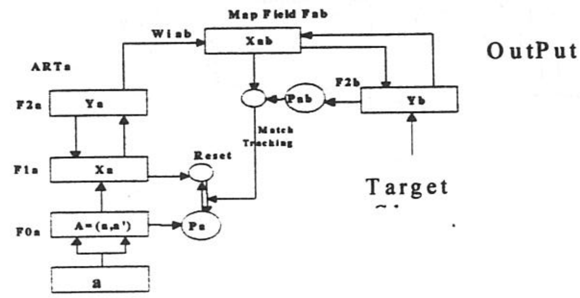


Fig.4. Fuzzy ARTMAP network for classification

4. Simulations

In order to test the algorithm for its effectiveness in predicting system security, we select a typical power system that is used in most studies. The 39 Bus New England power systems with 10 machines is tested as shown in figure (5). System configurations are available in [6], [7].

We study 6 cases in various situations and in each situation; effect of various conditions is considered. In cases of 1 through 5, we use Fuzzy ARTMAP Network and in case 6, a Perceptron Network is used. Finally the obtained results are compared.

In each case, performance error of neural network is calculated according to the following formula [6]:

$$E = \frac{1}{N}\left(\sqrt{\sum_{i=1}^{N}\left(y_{di} - y_{ai}\right)^{2}}\right) \qquad (11)$$

Where,
y_{di} : Desired output of NeuralNetwork.
y_{ai} : Actual output of Neural Network.
N : Number of Data Set for Training.

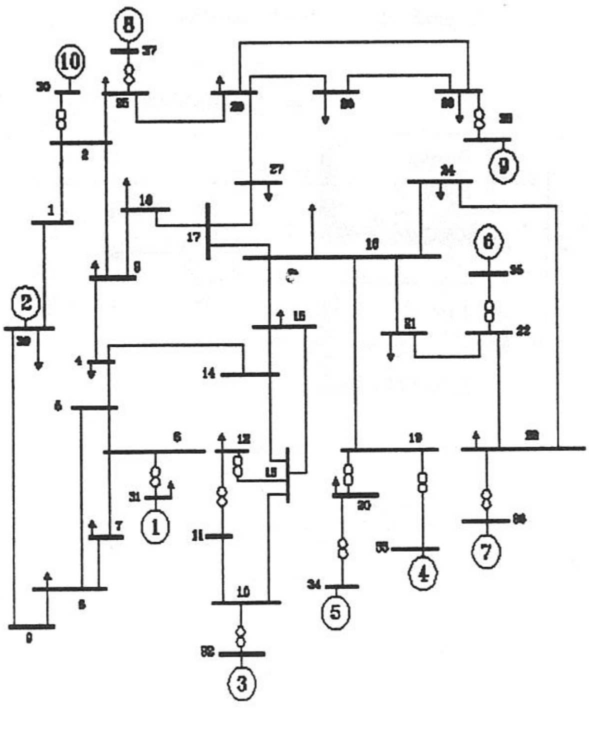


Fig.5. Typical power system

Case 1:
Using a step size of 0.05 for changing real power in both load buses and generation buses and finding critical eigenvalue, a set of 65 patterns was obtained off-line. In each step we used bus voltages ($|V_i|$, δ_i) as input bit pattern. These input bits and its respected critical eigenvalue make an input/output pair for neural network. These pairs were used to train the Fuzzy ARTMAP network. In this test, parameter ρ was chosen to be ρ_a=0.98, ρ_b=۰,۹۷, ρ_{ab}=۰,۹۶. A set of 6 training patterns was randomly selected from the above set. After training the network with 65 patterns, the set of 6 random patterns was used to test network. Summery of obtained results is given in table (1).

Training Error of this test is about 0.948% and is shown in figure (6).

Case 2:
In Another test we used the same number of data set, but we selected additional bit patterns as input. In this case, bus voltages and generating active power for generation buses and demanded active power for load buses ($|V_i|$, δ_i , Pg_i , Pd_i) are used as input bit patterns. Vigilance parameters are selected as above. Error obtained in this test is about 0.948% as it is seen; it is equal to Error obtained in case 1. The result is shown in figure (7).

Case 3:
In this test we used step size equal to 0.01, which creates more set of data (about 6400 set).

Also we used the same input bit patterns and the same Vigilance parameters with case 2. Error in this test is equal to 0.87%, which is a little lower than previous tests as it is shown in figure (8).

Case 4:
In this case we used 7800 set of data, and the input bit patterns are used as the one in test 1, it means $|V_i|$, δ_i. Vigilance parameters are selected as before. Error obtained in this test is the same as case 4 and is shown in figure (9).

Case 5:
In this case we used step size equal to 0.05 which creates 65 set of data. Also we used the same input bit patterns with case 2. But In this case, vigilance parameters are selected lower than before (ρ_a=0.93, ρ_b=0.92, ρ_{ab}=0.9). As it is shown in figure (10), error in this case is too higher than other cases.

Case 6 (Perceptron network):
In this case we used a 3-layer Perceptron Neural-Network with backpropagation method of training. Also we used the same input bit patterns. Error in this case is higher than the above cases and computing time for training is too high. A plot of error in this case is shown in figure (11).

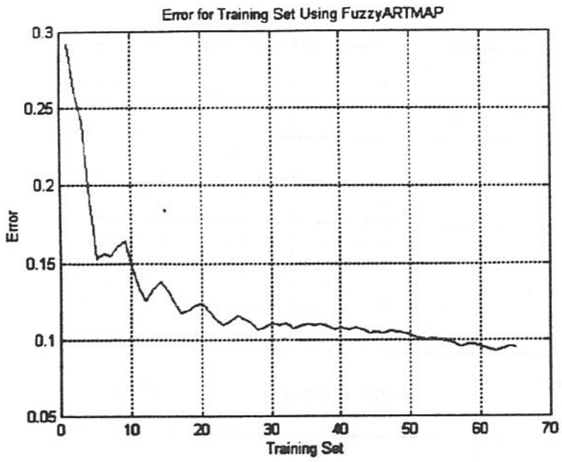


Fig.6. Error plot with 65 data set and V,delta as input (Case 1)

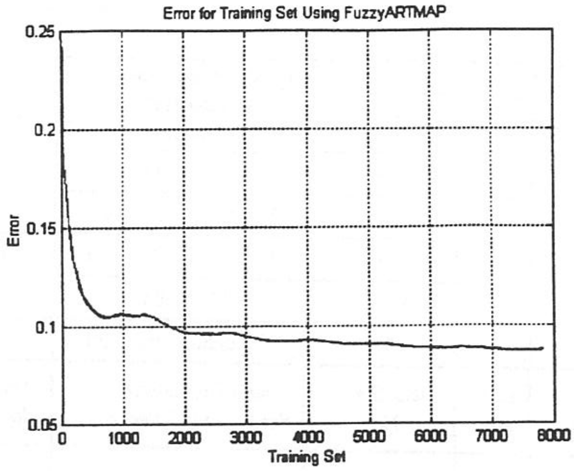


Fig.9. Error plot with 7800 data set and V,delta as input (Case 4)

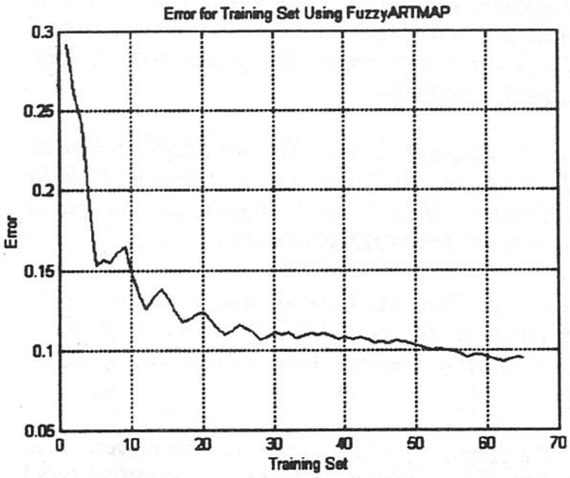


Fig.7. Error plot with 65 data set and V,delta,Pg,Pd as input (Case 2)

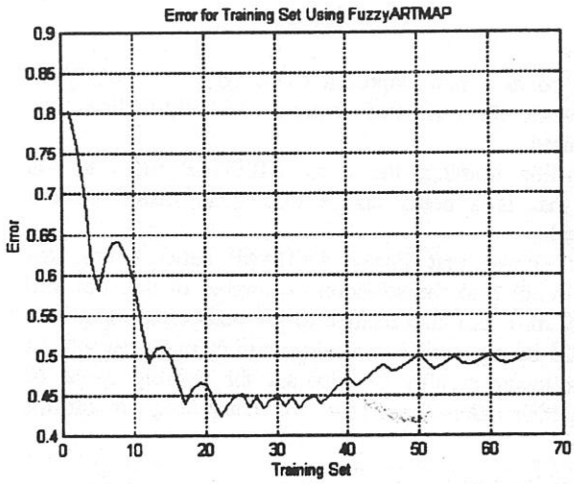


Fig.10. Error plot with 65 data set and V,delta ,pg,pd as input (Case 5)

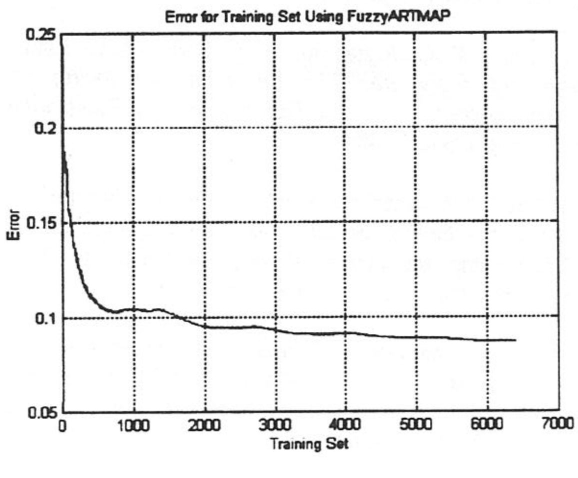


Fig.8. Error plot with 6400 data set and V,delta,Pg,Pd as input (Case 3)

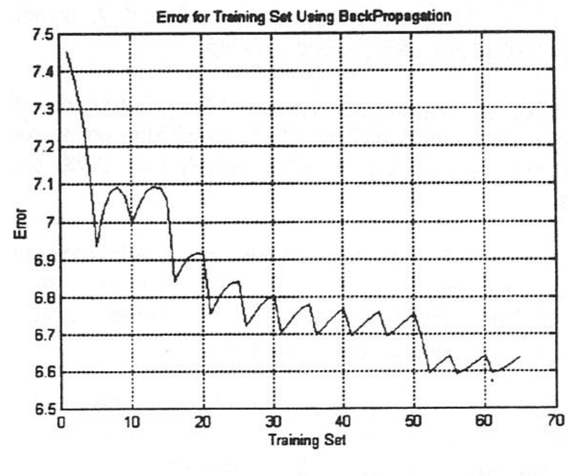


Fig.11. Error plot with 65 data set and V,delta,Pg,Pd as input (Case 6)

Table (1) Summery of Test Results

Network Type	Test No.	Data Set No.	Input Bit patterns For Neural Network	ARTa Node No.	ARTb Node No.	pa	pb	pab	% Error
Fuzzy ARTMAP	١	٦٥	V , delta	٢١	١٧	٠.٩٨	٠.٩٧	٠.٩٦	٠.٩٥ %
	٢	٦٥	V , delta , Pg , Pd	١٩	١٧	٠.٩٨	٠.٩٧	٠.٩٦	٠.٩٥ %
	٣	٦٤٠٠	V , delta , Pg , Pd	٤٢٠	٨٧١	٠.٩٨	٠.٩٧	٠.٩٦	٠.٨٧ %
	٤	٧٨٠٠	V , delta	٥١٨	١٠٦٠	٠.٩٨	٠.٩٧	٠.٩٦	٠.٨٧ %
	٥	٦٥	V , delta , Pg , Pd	٦	٤	٠.٩٣	٠.٩٢	٠.٩٠	٤.٩٠ %
٣ layers Percepteron	Test No.	Data Set No.	Input Bit patterns For Neural Network	Hidden Node No.	Neuron Type	Learning Rates			% Error
	٦	٦٥	V , delta , Pg , Pd	٢٥	BSF	n١ = n٢ = ٠.١			٦.٧٠ %

5. Conclusion

In this paper a new approach based on Fuzzy ARTMAP NeuralNetwork for estimated dynamic stability indices has been presented.

For on-line training, the fuzzy ARTMAP network was found to that is a better choice than other neural-network training method.

It was shown that Fuzzy ARTMAP network has low sensitivity relative to the selection of number of data set feed to it for training and also relative to the number of input bits. These could be regarded as an advantage of this network. As a result a lower number of data set for training could be selected which takes less time for computing in off-line mode.

References

[1] J.G. Francis, "*The QR Transformation-A Unitary Analogue to the LR Transformation*", part 1 and 2, comp. Journal, 4, 1961/62, pp. 256-271 and 332-345.

[2] S. Okubo, H. Suzuki, K. Uemura, "*Modal Analysis of power System Dynamic Stability*", IEEE transaction on power Apparatus and systems, Vol. PAS-97, July/August 1978, pp. 1313-1318.

[3] P. Kundur, P.L. Dandeno, "*Practical Application of Eigenvalue Techniques in the Analysis of power system dynamic stability problems*", Proc. Fifth Power System Computation Conference, England, September 1975.

[4] Y. Obata, S.Takeda, H.Suzuki, "*An Efficient Eigenvalue Estimation Technique for Multi-Machine Power System Dynamic Stability Analysis*", IEEE Transaction on Power Apparatus and System, Vol. PAS-100, Jan.1981, pp.259-263.

[5] M.E. Aggoune, L.E. Atlas, D.A. Cohn, M.J. Damborg, M.A. El-sharkawi, and R.J. Marks, "*Artificial Neural Networks for power system static security assessment*", IEEE Conference, 1989, PP 490-494

[6] H. Mori, Y. Tamaru, S. Tsuzuki, "*An Artificial Neural-Net Based Technique for Power System Dynamic Stability with the Kohonen Model*", IEEE transaction on power system, Vol. 7, No. 2, May 1992, PP 856-864.

[7] H. Assadi, A. Tan, M. Etezdi-Amoli, D. Egbert, M.S. Fadali, "*Application of the ARTMAP neural network to power system stability studies*", IEEE Conference, 1992, PP 1080-1085.

[8] G.A. Carpenter, S. Grossberg, N. Markuzon, J.H. Reynolds, D.B. Rosen, "*fuzzy ARTMAP: A Neural Network Architecture for Incremental Supervised Learning of Analog Multidimensional Maps*", IEEE transaction on neural networks, Vol. 3, No. 5, Sep. 1992, PP 698-713.

[9] Q.Y. Xuan, R.K. Aggarwal, Y.H. Song, A.T. Johns, "*Application of fuzzy ARTMAP for fault monitoring on complex transmission systems*", IEE Conference Publication No. 440, 7-9 July 1997, PP 88-93.

[10] T. Athay, V.R. Sherkey, R. Podmore, S. Virmani, C. Puech, "*Transient Energy Stability Analysis*", Conference on system Engineering for power: Emergency Operating State Control-Section 4, Davos, Switzerland, Sept. 1979.

[11] T. Athay, R. Podmore, S. Virmani, "*A practical Method for Direct Analysis of transient Stability*", IEEE Transaction on power Apparatus and Systems, Vol. PAS-98, No. 2, March/April 1979, PP. 573-584.

Biographies

Shahram Javadi received his B.Sc. degree in Electrical Engineering from Tehran Polytechnic University of Technology in 1992 and his M.Sc. degree in Power Engineering from Khaje-Nasire-Toosi University of Technology in 1995. He is currently working on his Ph.D. thesis on dynamic stability of power system using fuzzy ARTMAP network at Science & Research Center of AZAD University. He is also a member of IEEE and IAEE of IRAN.

Mehdi Ehsan received his B.Sc. and M.Sc. in Electrical Engineering from Tehran College of Tehran University in 1963, Ph.D. and DIC from Imperial College University of London in 1976. Since then, he has been with the Electrical Engineering Department of Sharif University of Technology in different responsibilities. He is currently a professor in Electrical Engineering Department and vice chancellor for academic affairs in Sharif University. He has an extended cooperation with research center in Tehran and also aboard. His research interests are power simulation, dynamic and transient stability, identification of expert systems of parameters and application of expert systems in power system operation and control.

Nasser Sadati was born in Iran, in 1960. He received the B.Sc. degree in Electrical Engineering from Oklahoma State University, Oklahoma in 1982 and the M.Sc. and Ph.D. degrees in Electrical Engineering from Cleveland State University, Cleveland Ohio, in 1985 and 1989, respectively.
From 1986 to 1987, he worked for NASA Lewis Research Center to study the Albedo effects on Space Station Solar Array. Since 1990 he has been with Sharif University of Technology, Tehran Iran, where he is currently an associate Professor at Electrical Engineering Department and Director of Intelligent Systems Laboratory.
He has published over 90 papers and currently working on three books in English and Persian. Modern Control Theory is now under publication.
His research interests involve Intelligent Control, Large Scale Systems and Pattern Recognition.