A Comparison Between Multilayer Perceptron and Fuzzy ARTMAP Neural Network in Power System Dynamic Stability

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Abstract: In this article, two different types of neural network architectures namely multilayer perceptron and Fuzzy ARTMAP neural network are compared in an application to a power system problem. In order to evaluate the ability of these two neural networks, the power system dynamic stability problem has been considered and the performance and deterioration of the proposed approaches have been investigated.
For evaluation of dynamic stability indices, a typical power system is tested and the results of Fuzzy ARTMAP appoach are compared with those obtained from classical multilayer perceptron. For on-line training, it is shown that the Fuzzy ARTMAP neural network outperforms the classical multilayer perceptron.

Keywords: Power Systems, Dynamic Stability, Perceptron,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 problem. In this paper, the stability is evaluated by calculating the eigenvalue of the system matrix in the linearized dynamic equation. More recently the application of neural network has been developed in many of engineering problems. One of these problems is determination of critical eigenvalue in a power system which has been done by multilayer perceptron approach [1] and KOHONEN neural network classifier [2].
In this paper, a different approach is proposed for dynamic stability assessment. This approach is based on Fuzzy ARTMAP neural network. Because of self-organized characteristic of these networks, they can be used in an 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 the power system is stable or not. It doesn't present any idea about stability indices.
This paper not only states the situation of power system from stability aspects but also computes the stability margin of a power system. In Section 2, a 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. In section 3, a multilayer perceptron architechture is intruduced. Section 4 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 5. Finally, the conclusions are drawn in section 6.

2. Dynamic Stability in power system

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 [4], 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:

$$\dot{x} = A_s x \qquad (1)$$

Where,

x: State variable vector

A_s: system matrix

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:

$$A_z = (A_s + hI)(A_s - hI)^{-1} \qquad (2)$$

Where,

A_z: transformed system matrix

I: unit matrix

h: positive real number

Equation (2) 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

$$\mu = \left|\lambda_z^M\right| \qquad (3)$$

Where ë$_z^M$ is the most critical eigenvalue of matrix A_z.

Therefore we have:

$$\begin{cases} \mu < 1 & \text{Stable} \\ \mu = 1 & \text{Critical Stable} \\ \mu > 1 & \text{Unstable} \end{cases} \qquad (4)$$

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):

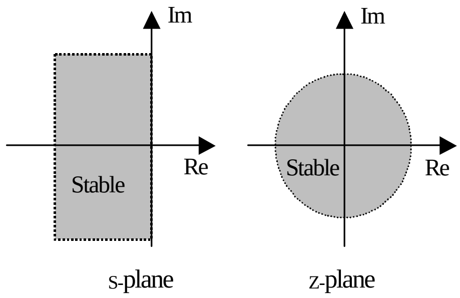

Fig.1. Stable Region of Eigenvalues in s-plane and z-plane

3. The Multilayer Perceptron

Multilayer perceptrons have been applied successfully to solve some difficult and diverse problems by training them in a supervised manner with a highly popular algorithm known as the error back-propagation algorithm. This algorithm is based on the error-correction learning rule. Figure (2) shows a typical three-layer perceptron architecture.

In order to avoid local minima and also have a stable network, we must pay attention to choosing initial conditions for weights. It is necessary to know that the number of neurons in hidden layer is an important problem. If it is too high, the error of neural network in training mode is low, but it is may be over learned. It means that in prediction mode, we must choose an optimum number of neurons in hidden layer and choosing a high number of neuron in hidden layer doesn't cause a good result.

So we face with a restricted architecture in multilayer perceptron.

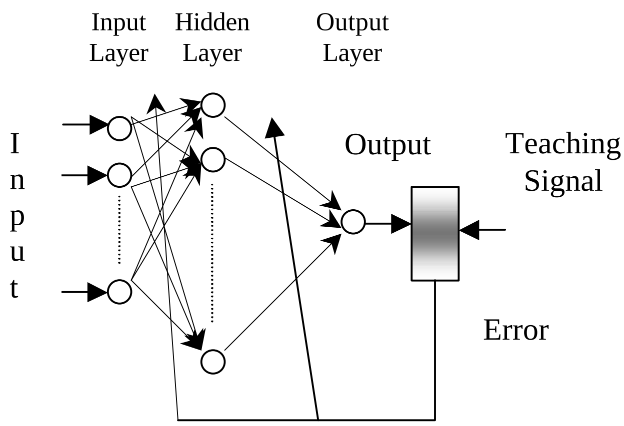

Fig.2. A typical 3-layer Perceptron architecture

4. 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 [5].

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).

Training algorithem of Fuzzy ARTMAP neural network is completely described in [4].

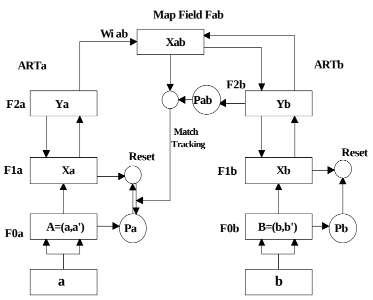

Fig.3. A typical Fuzzy ARTMAP architecture

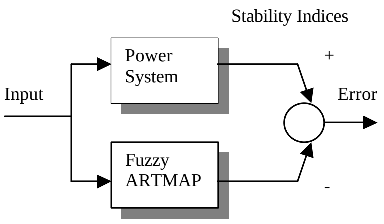

Fig.4. On-Line Training

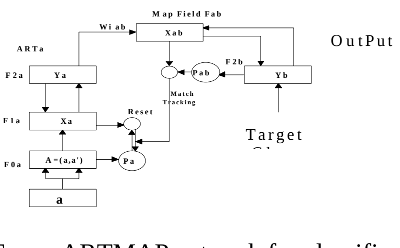

Fig.5. Fuzzy ARTMAP network for classification

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 system with 10 machines is tested as shown in figure (5). System configurations are available in [6], [7].

We study 6 case in various situations and in each situation, effect of various conditions is considered. In cases 1 through 3, a Perceptron neural network is used and in cases 4 through 6, we use Fuzzy ARTMAP neural network. Finally the obtained results are compared.

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 1000 patterns was obtained off-line. After training the network with 500 patterns, the set of remained 500 patterns was used to test network. Summery of obtained results is given in table (1).

In each step we used bus voltages ($|V_i|$, δ_i ,Pg_i, Qg_i) as input bit pattern. These input bits and its respected critical eigenvalue make an input/output pair for neural network.

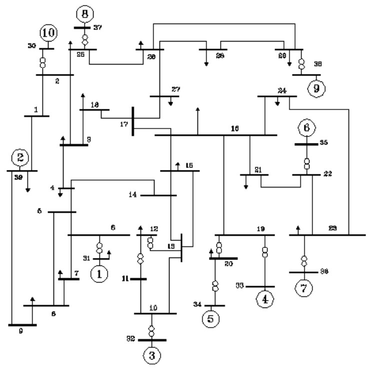

Fig.6. Typical power system

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.

Case 1 (perceptron network):
In this case we used a 3-layer perceptron neural network with backpropagation method of training. Each neuron is modeled by a USF (Unipolar Sigmoid Function). In this case tresholds aren't trained. After several tests it was found that the number of 25 neurons in hidden layer causes a good result in prediction mode. A plot of error in this case is shown in figure (7).

Case 2 (perceptron network):
In this case a 3-layer perceptron neural network with backpropagation method of training is used, but each neuron is modeled by a BSF (Bipolar Sigmoid Function). Also we used the same hidden nodes number and tresholds aren't trained. A plot of error in this case is shown in figure (8).

Case 3 (perceptron network):
In this case we used the same 3-layer perceptron neural network with USF model, but tresholds are trained. A plot of error in this case is shown in figure (9).

Case 4 (Fuzzy ARTMAP):
In this case we used a Fuzzy ARTMAP neural network. Parameter ñ was chosen to be $\tilde{n}_a$=0.98, $\tilde{n}_b$=0.98, $\tilde{n}_{ab}$=0.95. A set of 500 training patterns was randomly selected from the off-line set. Summery of obtained results is given in table (1).
Training Error of this test is about 0.13% and is shown in figure (10).

Case 5 (Fuzzy ARTMAP):
In this case we used the same Fuzzy ARTMAP neural network as the above, but we chose a lower vigilance parameter than before case ($\tilde{n}_a$=0.9, $\tilde{n}_b$=0.9, $\tilde{n}_{ab}$=0.85). As it is shown the node number in both ART module are less than before case and also error is higher than before case. Error plot is shown in figure (11).

Case 6 (Fuzzy ARTMAP):
In this case we used the same neural network, but vigilance parameters are selected lower than before ($\tilde{n}_a$=0.75, $\tilde{n}_b$=0.75, $\tilde{n}_{ab}$=0.7). As it is shown in figure (12), error in this case is too higher than other cases.
So we find the lower choise of vigilance parameter results the lower node number and as a result it causes fast computing but the higher error.

Table 1, Summery of Test Results

Network Type	Test No .	Data Set No .	Input Bit patterns For Neural Network	Hidden Node No .	Neuron Type	Learning Rates			% Error
3 layers Percepteron	1	1000	V , delta , Pg , Pd	25	USF	n1=n2=0.1 withouth treshold training			0.88 %
	2	1000	V , delta , Pg , Pd	25	BSF	n1=n2=0.1 withouth treshold training			0.85 %
	3	1000	V , delta , Pg , Pd	25	USF	n1=n2=0.1 with treshold training			0.88 %
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	4	1000	V , delta , Pg , Pd	123	8	0.98	0.98	0.95	0.13 %
	5	1000	V , delta , Pg , Pd	120	3	0.90	0.90	0.85	0.46 %
	6	1000	V , delta , Pg , Pd	84	3	0.75	0.75	0.70	0.55 %

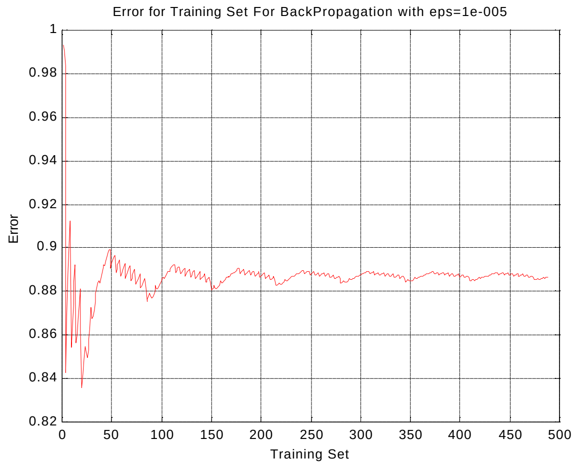

Fig.7. Error of MLP with USF functions treshold training (Case 1)

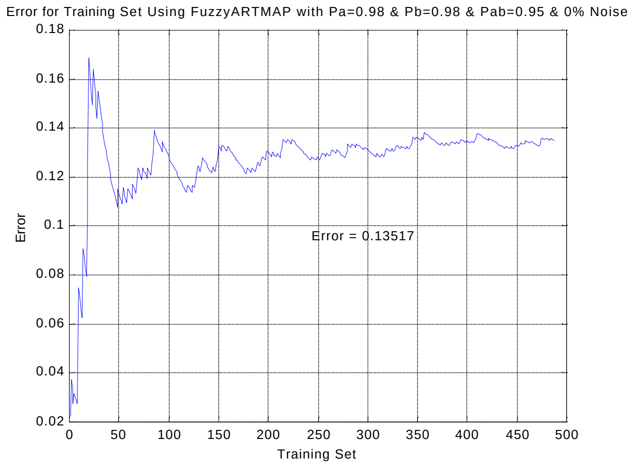

Fig.10. Error of Fuzzy ARTMAP with high vigilance parameter (Case 4)

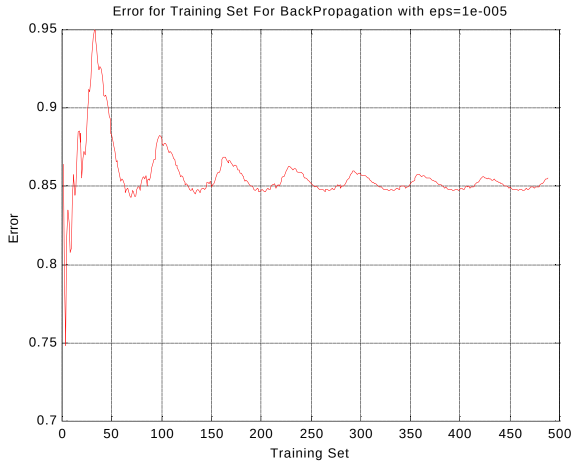

Fig.8. Error of MLP with BSF functions without treshold training (Case 2)

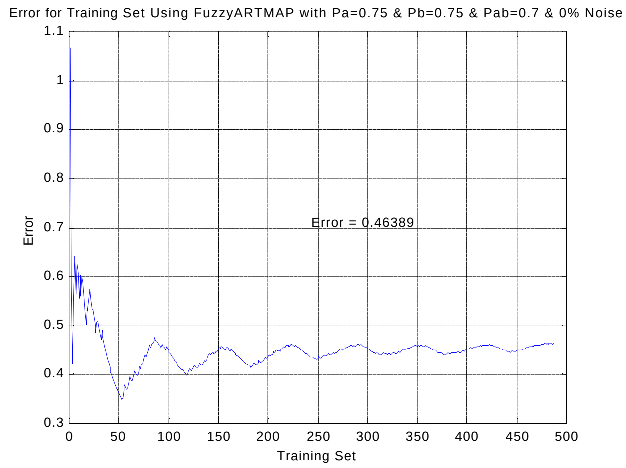

Fig.11. Error of Fuzzy ARTMAP with medium vigilance parameter (Case 5)

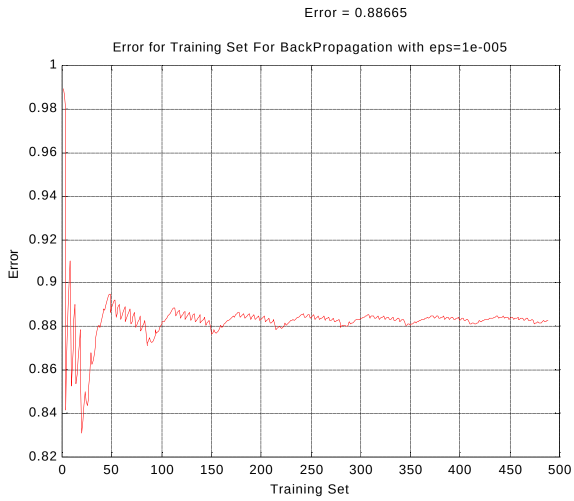

Fig.9. Error of MLP with USF functions include treshould trainig (Case 3)

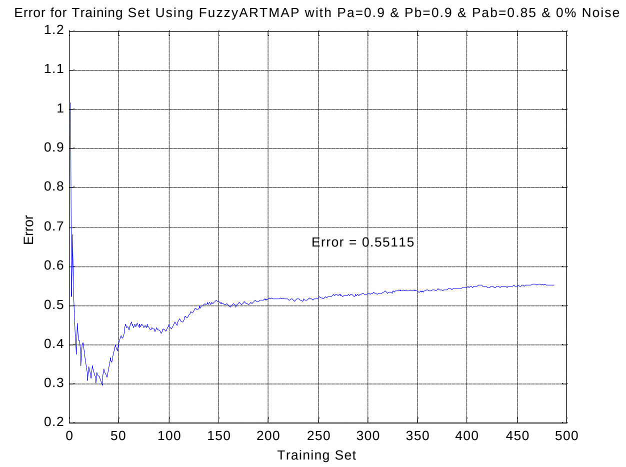

Fig.12. Error of Fuzzy ARTMAP with low vigilance parameter (Case 6)

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.

In addition in applications such as power system which its condition and also its construction varies several times, multilayer perceptron can not operates as well as Fuzzy ARTMAP, because in MLP we have a fixed structure for a pre-defined system. But Fuzzy ARTMAP neural network has self organized charactristic and it is a good condidate for solving power system problems.

Also in MLP if we don't choise a good initial condition for weights or a good hidden neuron number, we may be get bad results or the network may be unstable.

Also it is necessary to know that the number of neurons in hidden layer is an important problem. If it is too high, the error of neural network in training mode is low, but it is may be over learned. It means that in prediction mode, we must choose an optimum number of neurons in hidden layer and choosing a high number of neuron in hidden layer doesn't cause a good result.

The Fuzzy ARTMAP network is capable of having robust supervised incremental learning. It learns during its operation without forgetting the previous knowledge. They exhibit attractive properties such as the ability to operate in non-stationary environments and to learn continuously new associations following training, without disrupting previous learning.

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