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Improvement of multi-machine power system stability using artificial intelligent power system stabilizer

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ABSTRACT

In this paper a Power System Stabilizer (PSS) is developed with Artificial Intelligent techniques to damp the low frequency oscillations thereby improve the stability of multi machine power system. To damp the low frequency oscillations lead- lag, fuzzy and artificial neural network power system stabilizers were designed for single machine connected to infinite bus and 4-machine, 11-bus system. From the result it was observed that conventional controllers such as lead–lag PSS cannot be applied at all operating points which also gives a slow response. Fuzzy Logic PSS (FLPSS) will give better and faster response compared to the conventional controller. Artificial Neural Networks (ANN) give the superior damping characteristics compared to remaining controllers. The performance of the each and every individual controller is analyzed in terms of Integral absolute error, Integral squared error, peak value and settling time of the response. ANN gives better response in all aspects and the simulation is carried out in MATLAB environment.

1. INTRODUCTION

Power system stabilizers [1] are used to minimize the low-frequency oscillations especially in the interconnected power system. It is mainly used to damp the oscillations in the range of 0.2 to 2 Hz and mainly generates mechanical torque opposite to the rotor oscillation in the case of disturbances such as small load variations, line outages, large and sudden disturbances such as a three phase fault. Damping of the rotor oscillations not only increases the transmission capability of the transmission line, but also enhances the stability of the multi-machine system.

In [2] it was clearly given a comparative study of conventional controllers such as PID and lead-lag PSSs. These controllers are extensively used for damping purpose because of simple in structure and low cost. The main drawback of these controllers is they will operate only at the fixed operating point, they are unable to provide dynamic response and also tuning of parameters of these controllers also difficult.

. In order to avoid the drawbacks in the above controllers adaptive control techniques [3] were developed where parameters will be adjusted automatically in the online according to the situation. The major drawback of these controllers is a real time prediction of the model is required which is time consuming.

Later Fuzzy Logic PSS was developed to avoid the draw back in adaptive control methods where real time prediction of model is not required. A fuzzy logic controller uses fuzzy logic, which is multivalued logic [4] and has been used as an alternative for conventional controllers but the design of input, output membership functions and rule base is difficult.

In this paper Artificial Neural Network is developed to directly damp the deviation in speed. Recently ANNs have been effectively used for different power system problems such as dynamic and transient stability analysis, power system security, and contingency studies etc. Design of ANN is easy if the training patterns are available. To demonstrate the superiority of the neural network controller, ANNPSS is trained with a set of training data and used in the above said test systems.

2. TEST SYSTEMS AND CONVENTIONAL POWER SYSTEM STABILIZER

Single machine infinite bus (SMIB) and two area four machine power systems [5-6] are considered as the test systems. Whenever there is a disturbance, whether it is a small or large the first parameters being changed are frequency and voltage. Both test systems are as shown in Figure1 and Figure3.

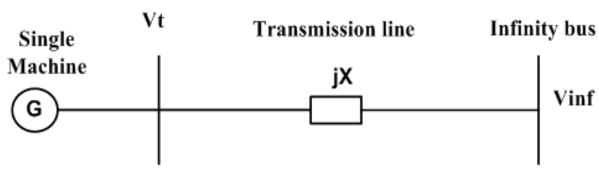

Figure 1. SMIB power system

The above system is linearized around an operating point as the power systems are nonlinear in nature. The state space formulation can be expressed as follows.

$$\Delta \dot{\delta} = \omega_0 \Delta\omega \tag{1}$$

$$\Delta \dot{\omega} = \frac{1}{M}(-K1\Delta\delta - D\Delta\omega - K2\Delta E'q) \tag{2}$$

$$\Delta E_q' = \frac{1}{T_{do}'}\left(-K4\Delta\delta - \frac{\Delta E'q}{K_3} + E_{FD}\right) \tag{3}$$

$$\Delta \dot{E}_{FD} = \frac{1}{T_A}(-K_A K_5 \Delta\delta - K4K6\Delta E'q - \Delta E_{FD} + K_a u) \tag{4}$$

In matrix form as follows

$$\dot{X}(t) = AX(t) + Bu(t) \tag{5}$$

where

$$A = \begin{bmatrix} 0 & \omega_0 & 0 & 0 \\ \frac{-k1}{M} & \frac{-D}{M} & \frac{-k2}{M} & 0 \\ \frac{-k4}{T'do} & 0 & \frac{-1}{k3T'do} & \frac{1}{T'do} \\ \frac{-k_a k_5}{T_A} & 0 & \frac{-k_a k_6}{T_A} & \frac{-1}{T_A} \end{bmatrix}$$

$$B = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{K_A}{T_A} \end{bmatrix} \quad X = \begin{bmatrix} \Delta\delta \\ \Delta\omega \\ \Delta E'q \\ \Delta E_{FD} \end{bmatrix}$$

The diagram of the SMIB with different power system stabilizers are as shown in Figure 2.

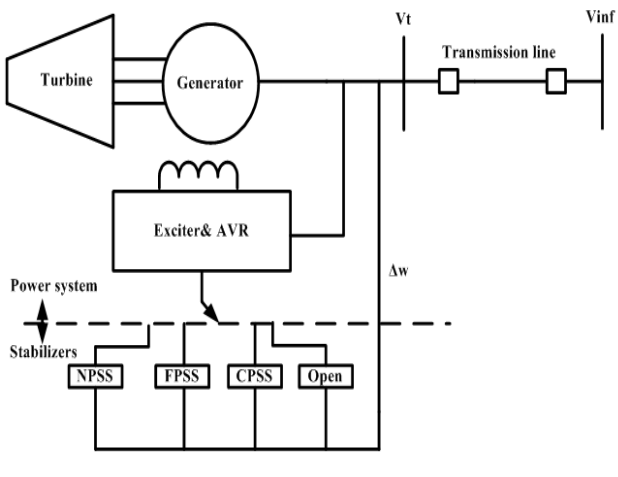

Figure 2. SMIB with different power system stabilizers

The other test case is 4-Machine and 11-bus power system as given in Figure 3

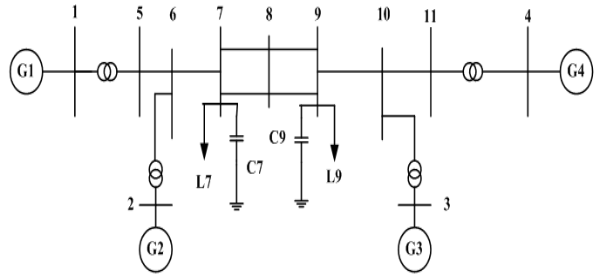

Figure 3. 4-machine, 11-bus power system

2.1 Conventional Power system Stabilizer (CPSS)

Lead-Lag PSS is also called as Conventional Power System Stabilizer. It will damp out the deviation of the frequency of the rotor by providing electrical torque opposite to those oscillations. It is well known fact that high gain AVR with fast acting exciter lead to oscillatory instability in the system which is characterized by the low frequency oscillation. This instability may affect the security and power transfer limit of the power system. These are designed using the linear model of the power system.

The SMIB system is first linearised based on assumptions and the stabiliser is designed, so it can be applicable around a fixed operating point and only for small disturbances such as load variations.

The lead-lag power system stabilizer mainly consisting of the following blocks. Stabilizer constant block, phase compensation block, and washout block. Stabilizer constant is the measure of damping provided by the stabilizer.

Most of the times the value of gain is set to maximum damping. While applying the PSS [7-8] care should be taken in such a way that it should not deteriorate the stability of the overall system. Washout block serves as a filter, it allows controller only to respond speed variations and without it the PSS may modify the terminal voltage which is undesirable.

The phase compensation block provides the required phase lead required to compensate the phase lag between the exciter input and the generator electrical torque. The diagram of the power system stabilizer is as shown in Figure 4

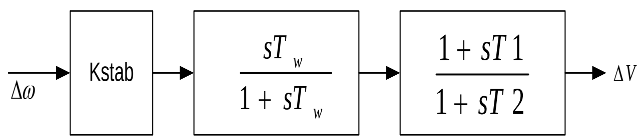

Figure 4. Conventional power system stabilizer

3. DESIGN OF FUZZY POWER SYSTEM STABILIZER (FPSS)

FLC uses multi valued logic, whereas classical logic is a two valued logic and it can be conveniently applied to the problems where the uncertainty in the problem defined or the data is insufficient and it can be useful even exact mathematical model is not available.

It can effectively represent the inexact or approximate nature of real world problems. Fuzzy logic is much nearer to human thinking compared to classical logic system. It provides an algorithm which will convert the crisp control strategy in automatic or fuzzy control strategy.

FLC uses three steps such as fuzzification, defuzzification and fuzzy inference for its control operation. Fuzzification is nothing but the conversion of linguistic variables into fuzzy membership [9-10] functions which will be only understood by the controller. Fuzzy inference is nothing but implying rules from rule base on input membership functions to get output. Defuzzification is the conversion of aggregated fuzzy output into a crisp value. FLC will have two inputs such as change in speed, change in acceleration and one output such as change in voltage. From the available shaft speed ($\Delta\omega$) the acceleration signal is deduced using Eq.6.

$$\Delta \dot{w}(k) = (\Delta\omega(k) - \Delta\omega(k-1)) / \Delta T \quad (6)$$

where ΔT is the sampling interval. Block diagram of FLC is as shown in Figure 5

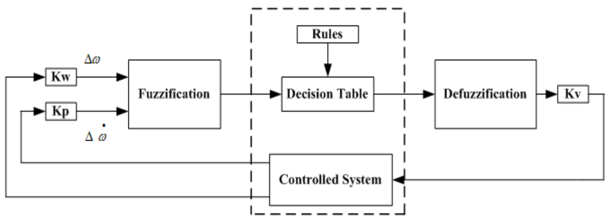

Figure 5. FLC block diagram

FLC in MATLAB software can be represented as sown in Figure 6.

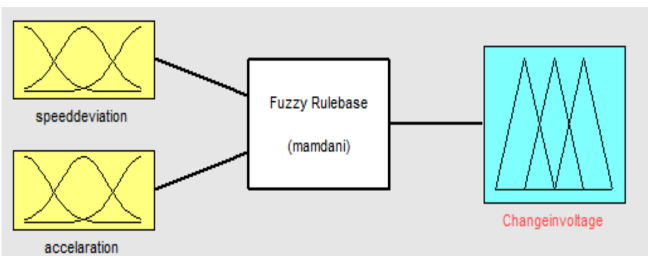

Figure 6. FLC representation in matlab software

The input membership functions are deviation in speed and the derivation in acceleration which are as given in Figure 7 & Figure 8

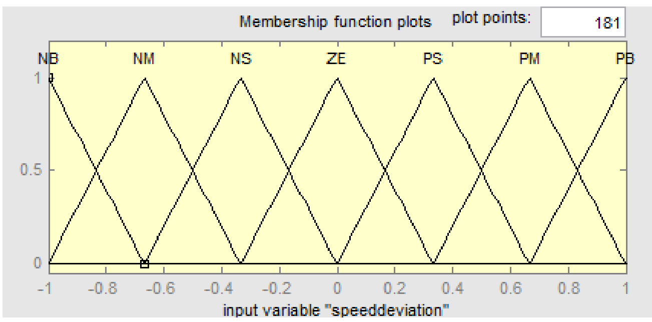

Figure 7. Membership function of speed deviation

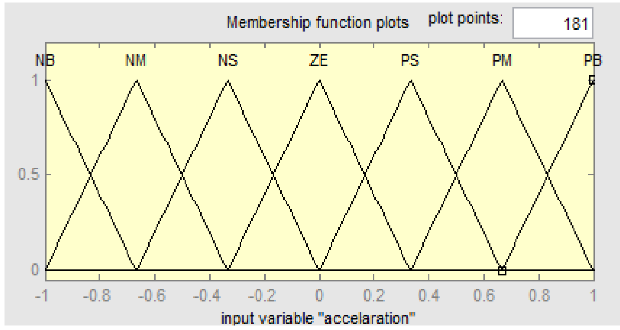

Figure 8. Membership functions of acceleration

Rule base where set of rules are present to get optimum output are as given in Table 1

Table 1. Rule base of FLC

$\Delta\alpha$ / $\Delta\omega$	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NS	ZE	ZE	PS
NM	NB	NB	NM	NS	ZE	PS	PM
NS	NB	NB	NM	ZE	PS	PM	PB
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NB	NM	NS	ZE	PM	PB	PB
PM	NM	NS	ZE	PS	PM	PB	PB
PB	NS	ZE	ZE	PS	PB	PB	PB

Using Mamadani fuzzy inference system set of rules is implied on the input membership function to determine the response [11-12]. The output membership function is as shown in Figure 9

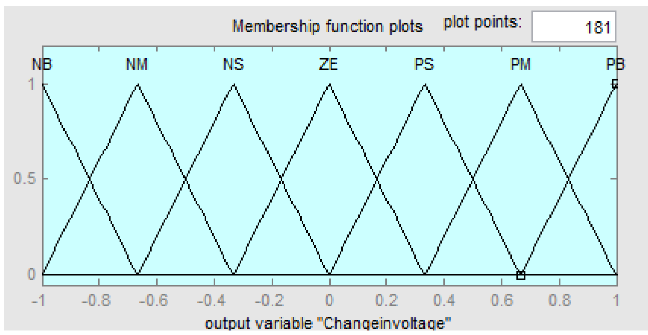

Figure 9. Membership functions of voltage

The Fuzzy logic controller can be applied to different applications such as controller in control systems, Decision making, Pattern recognition etc.

4. DESIGN OF ARTIFICIAL NEURAL NETWORK CONTROLLER

ANNs [13-14] are designed to emulate the characteristics of the human brain. It is the interconnection of different fundamental elements called as neurons, which are the processing elements of the network. Neural networks allow massive parallel processing so that they can be applied to complex problems also.

At the input of each neuron activation value which is also called the weighted sum of all the signals will be calculated which is processed through activation function to determine the output. Different variety of neural networks are available out of which multilayer feed forward networks, self organizing networks, and Hopfield networks are most popular networks and multilayer networks are most suitable for different applications.

Multilayer neural networks [15-16] can be conveniently used for both linear separable and linear non separable problems. Multilayer neural networks are trained by backpropagation algorithm. The architecture of the Feed forward backpropagation neural network as show in Figure 10 which contains one input layer which contains one neuron, one hidden layer which contains 10 neurons and one output layer which contains single neuron. The number of hidden layers increases the accuracy of the training increases, but complexity of the system increases.

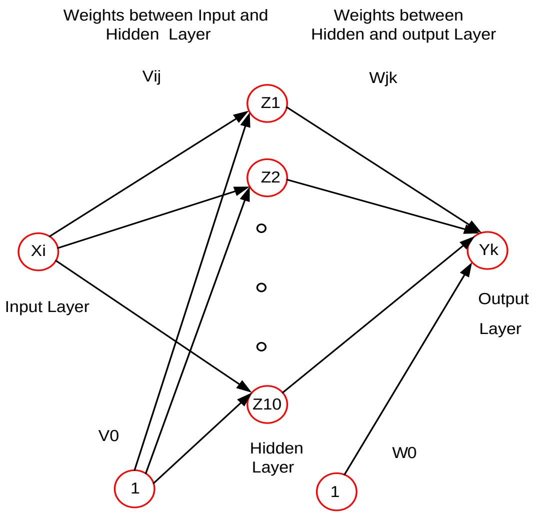

Figure 10. Proposed back propagation neural network

Vij= Weights between input and hidden layer.
Wjk=Weights between hidden and output layer.
Xi= Input to the Neural Network.
Yk= Output of the Neural Network.
V0= Weights between bias neuron and hidden layer.
Wo= Weights between bias neuron and output layer.

Backpropagation [17-18] provides step by step procedure to train multilayered neural network. The Algorithm uses generalized delta-learning rule, known as back propagation rule. It gives efficient method for updating the weights. Being gradient descent method it minimizes squared error. In this algorithm, supervisory learning is used and weights are adjusted till the balance between the output value and the target value is balanced. Using the Back propagation algorithm [19-20] the outputs of each layer and weights adjustment can be calculated as follows.

The weighted sum or activation value of each unit in the hidden layer can be calculated as

$$Z_{-inj} = Voj + \sum_{i=1}^{n} (X_i * V_{ij}) \tag{7}$$

If it is processed through sigmoid activation function we will get the output of each hidden layer neuron.

$$Z_j = f(Z_{-inj}) \tag{8}$$

The activation value and the output of the output layer can be calculated using the Eqn. & Eqn.

$$Y_{-inj} = W_{ok} + \sum_{j=1}^{p} (Z_j * W_{jk}) \tag{9}$$

$$Y_k = f(Y_{-inj}) \tag{10}$$

The output of each neuron is compared with the target output and the error is calculated.

$$\Delta Y_k = (t_k - y_k) * f(Y_{-ink}) \tag{11}$$

The weights between output and hidden layer, hidden layer and the input layer will be adjusted to minimize the error as given in Eq.12

$$\begin{aligned} W_{ik}(new) &= W_{ik}(old) + \Delta W_{jk} \\ W_{ok}(new) &= W_{ok}(old) + \Delta W_{ok} \\ V_{ij}(new) &= V_{ij}(old) + \Delta V_{ij} \\ V_{oj}(new) &= V_{oj}(old) + \Delta V_{oj} \end{aligned} \tag{12}$$

The proposed neural network consists of a single input such as deviation in speed and single output such as change in voltage. Input layer consists of single neuron, hidden layer consists of 10 neurons and the output layer contains single neuron as shown in Figure 11

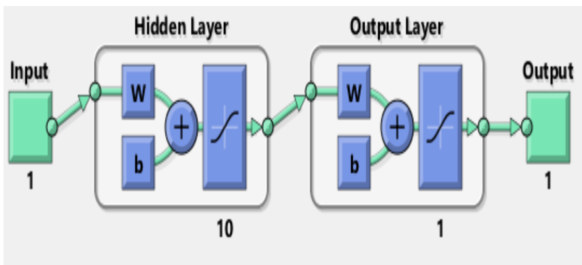

Figure 11. Proposed multilayer neural network

Neural networks are mainly used for the control applications, forecasting applications, data compression and optimization etc.

Around 568 patterns are developed from fuzzy logic power system stabilizer have been developed to train the neural network. Once the neural network is trained it will act as a controller and can minimize the error. The regression analysis of training which represents the effectiveness of training is as given in Figure 12.

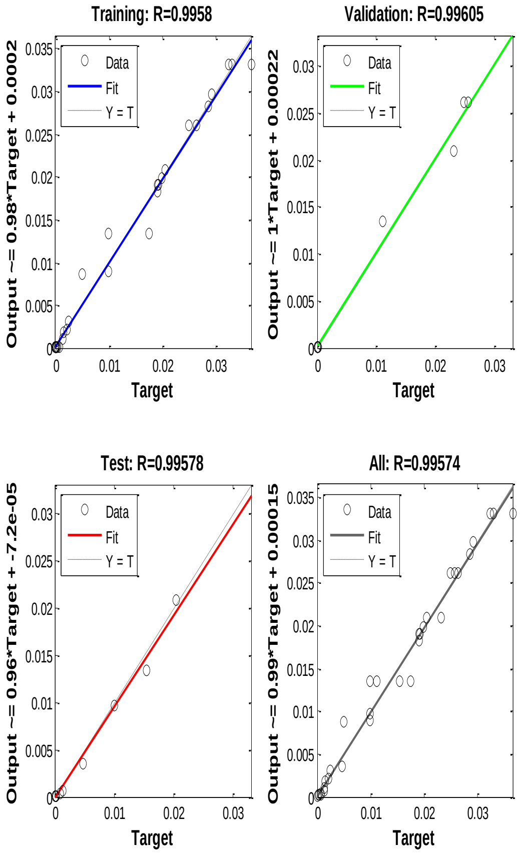

Figure 12. Regression analysis of neural network

5. RESULTS

Step load disturbance of 0.01 p.u and 0.1 p.u is applied to a single machine connected to the infinite bus. Because of the disturbances there is variation in rotor frequency which should be damped out quickly to restore the rotor angle stability. Lead-Lag PSS, Fuzzy PSS and Artificial neural networks are used to damp out the oscillations. The change in frequency with the disturbance and different controllers are as sown in Figure 13 and Figure 14.

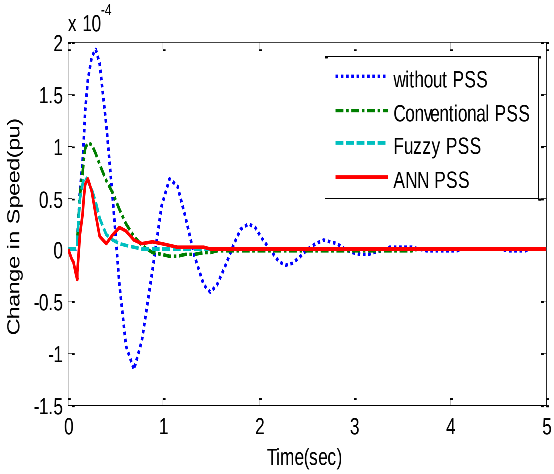

Figure 13. Change in frequency without and with controllers at a step disturbance 0.01 p.u

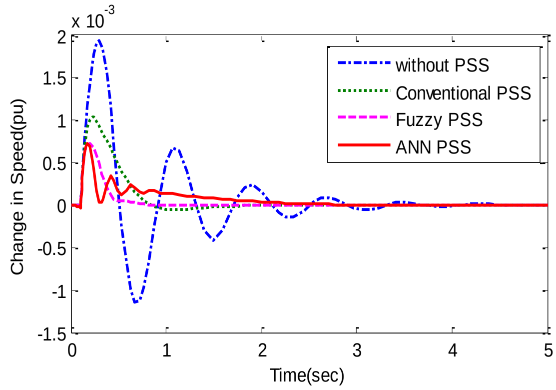

Figure 14. Change in frequency without and with controllers at a step disturbance 0.1 p.u

Integral Absolute Error(IAE) and Integral Squared Error(ISE) are calculated and it was clearly observed that controller by controller both errors is decreasing as given in Table 2 & Table 3.

Table 2. Errors with respect to controllers with a step change of 0.01

$\Delta Te = 0.01$	IAE	ISE
W/o	0.0015	1.49E-07
Conventional	8.35E-04	5.98E-08
Fuzzy	7.05E-04	3.78E-08
ANN	4.47E-04	1.64E-08

Table 3. Errors with respect to controllers with step change of 0.1

$\Delta Te = 0.1$	IAE	ISE
W/o	0.0167	1.64E-05
Conventional	0.0086	6.16E-06
Fuzzy	0.0083	3.58E-06
ANN	0.0066	2.12E-06

In a single machine infinite bus with small disturbance how the system behavior is changing and how effectively controllers can damp out the small frequency oscillations observed nothing steady state stability is improved. The effectiveness controllers when there is a large disturbance such as a three-phase fault occurs will be observed on four machines and 11 bus test system. The response of the system with three phase fault without power system stabilizer is as given in Figure 15.

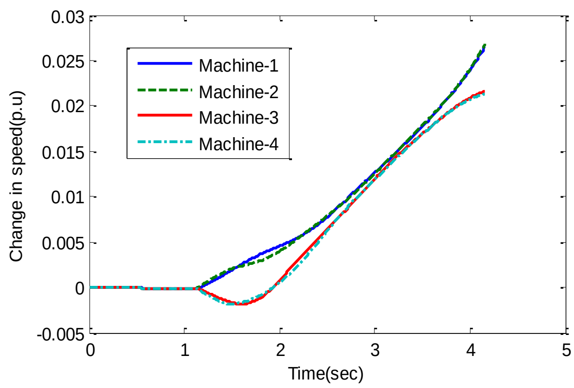

Figure 15. Change in speed of all machines without PSS

In Figure 13 it was clearly observed that with the three-phase fault change in speed of all machines changes in an uncontrolled manner and now it needs to observe how the controllers bring back this uncontrolled oscillation to normal state. Speed deviation of all four machines with Lead-Lag, Fuzzy and ANN power system stabilizers are as shown in Figure 16, Figure 17 and Figure 18.

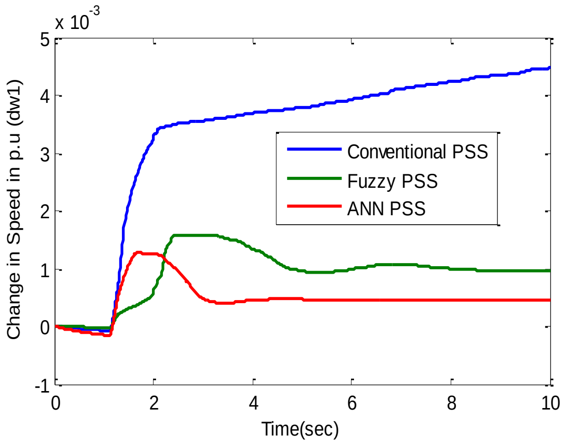

Figure 16. Speed deviation of machine-1 with different controllers

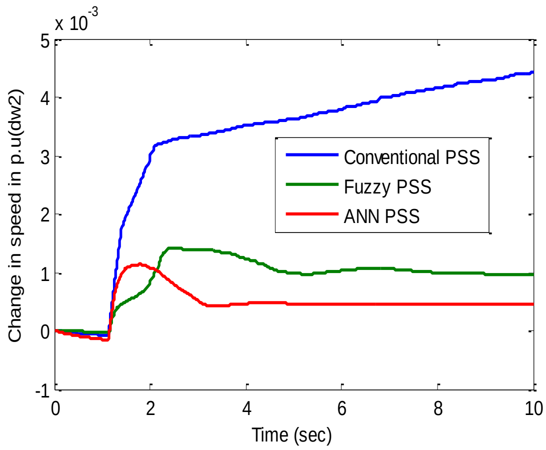

Figure 17. Speed deviation of machine-2 with different controllers

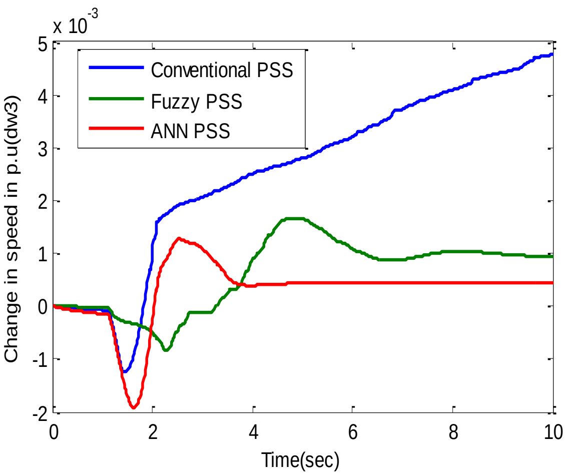

Figure 18. Speed deviation of machine-3 with different controllers

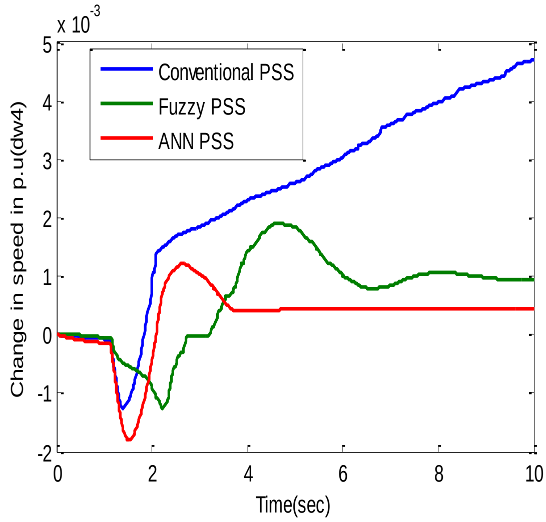

Figure 19. Speed deviation of machine-4 with different controllers

The Integral Error and Squared Error without and with controllers as shown in the Table 4

Table 4. Variation of integral and squared error without and with controllers

		WOPSS	CPSS	FPSS	ANNPSS
G1	IAE	0.0239	0.0046	0.001	4.67E-04
	ISE	5.72E-04	2.11E-05	1.08E-06	2.18E-07
G2	IAE	0.024	0.0045	0.001	4.65E-04
	ISE	5.78E-04	2.07E-05	1.06E-06	2.16E-07
G3	IAE	0.0209	0.0037	9.65E-04	4.37E-04
	ISE	4.36E-04	1.40E-05	9.32E-07	1.91E-07
G4	IAE	0.0207	0.0038	9.86E-04	4.36E-04
	ISE	4.28E-04	1.41E-05	9.71E-07	1.90E-07

From the Table 4 it is clear that the neural network can effectively damp the low frequency oscillations in all machines.

6. CONCLUSION

In this paper controllers are designed to damp out the low frequency oscillations in the power system when there is steady state and transient disturbances. Step disturbance is applied to the single machine connected to infinite bus and observed the low frequency oscillations which are increasing with the magnitude of disturbance. Mostly the effect of low frequency oscillations will be in interconnected, multi-machine system rather than SMIB system. So 4-machine, 11-bus interconnected power system is considered as another test system. A 3-phase fault is created on the transmission line and it was observed that in all the four machines the deviation in frequency is uncontrollable. To damp out the low frequency oscillations during disturbance conditions first lead lag compensator is used which is conventional controller and the response is better when compared to without a controller. But this controller can be effectively operated at a fixed operating point only. Another controller considered is fuzzy controller, which gives good response compared to conventional stabilizer, but design is little bit difficult. It was observed that the Artificial Neural network provides excellent damping capabilities compared to other controllers in terms of Integral Absolute and Integral Squared Error.

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