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Research Paper

DAMPING OF LOW FREQUENCY OSCILLATIONS WITH UPFC AN APPLICATION OF NEURO-FUZZY CONTROLLER

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The paper presented here is dedicated to design of Neuro-Fuzzy controller for damping Low Frequency Oscillations (LFO) for Unified Power Flow Controller (UPFC). LFO occur in power system because of Lack of balance between electrical power and mechanical power. Traditionally Power System Stabilizers (PSS) can be used to damp LFO but with the introduction of Facts devices Such as UPFC which has future advantage of increase transient stability and reduce sub-synchronous resonance along with damping LFO. So UPFC can be used to damp LFO Instead of PSS. In this paper mathematical model of Single Machine Infinite Bus (SMIB) with UPFC will be designed. For controlling UPFC, PSS and Neuro-Fuzzy controllers were designed and simulated for different faults. Results show good performance of neuro-fuzzy controller.

Keywords: Neuro-Fuzzy controller, Low Frequency Oscillations (LFO), Unified Power Flow Controller (UPFC), Single Machine-Infinite Bus (SMIB)

INTRODUCTION

The demand for electrical energy is growing day by day and because of this the transmission lines are loaded to their full capacity and this has increased the occurrence of LFO. Low frequency oscillations (LFO) occur in power system because of unbalance between electrical power and mechanical power and this may cause to partial or full black out of system.

Earlier PSS was used to damp LFOs but now a day, but with the introduction of FACTS devices they are used to damp LFO. FACTS controllers have capability to control network conditions quickly and these features can be used to improve power system stability, reduce sub-synchronous resonance.

UPFC (Hingorani and Gyugyi, 2000; Wang and Swift, 1997; and FACTS, 1999) is Fact device that can be used to damp LFO. It damps LFO by controlling power flow. The UPFC consists of voltage source converters, one connected in series and the other in shunt and both are connected back-to-back through a DC

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Capacitor. Both voltage source converters performance is controlled by pulse width modulation where m_E, m_B and δ_E, δ_B (Gyugyi *et al.*, 1995) are amplitude modulation ratio and phase angle of the reference voltage. Here mathematical model of linear and dynamic (Wolanki *et al.*, 1997; Noroozian *et al.*, 1997; Nabavi-Niaki and Iravani, 1996; Smith *et al.*, 1997; and Wang, 1998) UPFC is presented. Mathematical model of modified heffron-philips model installed with UPFC is presented (Kundur, 1994; Banejad *et al.*, 2008; and Dash *et al.*, 2000). For a system without PSS, excellent damping is achieved with proper design of UPFC controller.

In recent years, there are many methods by which we can generate control signals to UPFC. They are Fuzzy control (Dash *et al.*, 2000; Oudalov *et al.*, 2001; and Karbalaye et al., 2009), genetic algorithm approach (Khan *et al.*, 2003), conventional lead-lag control (Tambey and Kothari, 2003) and robust control methods (Ruban Deva Prakash and Kesavan Nair, 2007; Jang-Cheol Seo Seung-Il Moon Jong-Keun Park Jong-Woong Choe, 2001; and Rahim and Al-Baiyat, 2004).

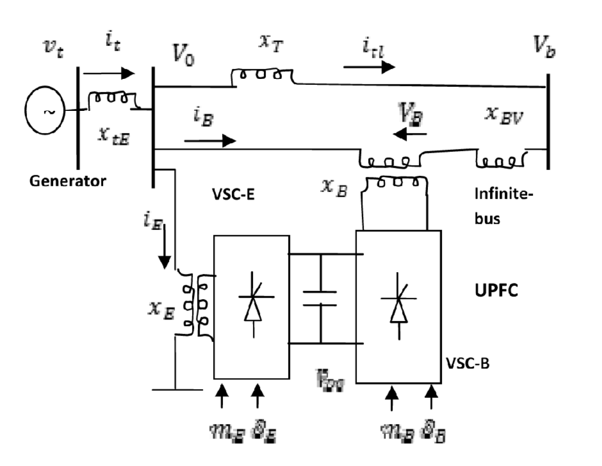
In this paper Adaptive Neuro Fuzzy Interface Systems (ANFIS) (Jyh-Shing Roger Jang, Chuen-Tsai Sun and Eiji Mizutani, 1997) is used to generate control signals to UPFC. Applying neural networks has several advantages such as fault tolerant capacity, ability to adapt to changes, recovery capability, high speed processing because of parallel processing and ability to build a DSP chip with VLSI technology. Here performance of Neuro-fuzzy controller is compared with PSS and simulation results was shown.

The organization is as follows: in section II modeling of power system with UPFC is studied. Designing of PSS is given in sections III. Hybrid learning method is given in section VI and designing of neuro fuzzy controller is given in V and Simulation results is given in section VI and finally conclusion is given in section VII.

MODEL OF POWER SYSTEM WITH UPFC

In this section we study single machine infinite system (SMIB) installed with UPFC as seen in the Figure 1.

Figure 1: A Single Machine Connected to Infinite Bus With UPFC



It is assumed that UPFC is employing pulse width modulation. In Figure 1 m_E, m_B and δ_E, δ_B are amplitude modulation ratio and phase angle of the reference voltage of each voltage source converter respectively. Here a linear model of power system is studied. In order to consider the effects of UPFC in damping LFO dynamic model of UPFC is taken. Here we are neglecting resistances.

$$\delta = \omega_0 \Delta\omega \quad ...(1)$$

The dynamic equations of power system are

$$\dot{\omega} = P_m - P_e - D\omega / M \quad ...(2)$$

$$E_q' = \left(-E_q + E_{fd}\right) / T_{d0}' \quad ...(3)$$

$$E_{fd} = -\frac{1}{T_A} E_{fd} + \frac{K_A}{T_A}\left(v_{t0} - v_t\right) \quad ...(4)$$

The dynamic equations of UPFC are

$$\begin{bmatrix} v_{Etd} \\ v_{Etq} \end{bmatrix} = \begin{bmatrix} 0 & -x_E \\ x_E & 0 \end{bmatrix} \begin{bmatrix} i_{Ed} \\ i_{Eq} \end{bmatrix} + \begin{bmatrix} \dfrac{m_E v_{dc} \cos \delta_E}{2} \\ \dfrac{m_E v_{dc} \sin \delta_E}{2} \end{bmatrix} \quad ...(5)$$

$$\begin{bmatrix} v_{Btd} \\ v_{Btq} \end{bmatrix} = \begin{bmatrix} 0 & -x_B \\ x_B & 0 \end{bmatrix} \begin{bmatrix} i_{Bd} \\ i_{Bq} \end{bmatrix} + \begin{bmatrix} \dfrac{m_B v_{dc} \cos \delta_B}{2} \\ \dfrac{m_B v_{dc} \sin \delta_B}{2} \end{bmatrix} \quad ...(6)$$

$$\dot{v}_{dc} = \frac{3m_E}{4C_{dc}} \begin{bmatrix} \cos \delta_E & \sin \delta_E \end{bmatrix}$$

$$= \begin{bmatrix} i_{Ed} \\ i_{Eq} \end{bmatrix} + \frac{3m_B}{4C_{dc}} \begin{bmatrix} \cos \delta_B & \sin \delta_B \end{bmatrix} \begin{bmatrix} i_{Bd} \\ i_{Bq} \end{bmatrix} \quad ...(7)$$

Combining all the above Equations (1) to (7) we get

$$\begin{bmatrix} \Delta \dot{\delta} \\ \Delta \dot{\omega} \\ \Delta E_q' \\ \Delta E_{fd}' \\ \Delta v_{dc}' \end{bmatrix} = \begin{bmatrix} 0 & \omega_0 & 0 & 0 & 0 \\ -\frac{k_1}{M} & -\frac{D}{M} & -\frac{k_2}{M} & 0 & -\frac{k_{pd}}{M} \\ -\frac{k_4}{T_{do}'} & 0 & -\frac{k_3}{T_{do}'} & \frac{1}{T_{do}'} & -\frac{k_{qd}}{T_{do}'} \\ -\frac{k_A k_5}{T_A} & 0 & -\frac{k_A k_6}{T_A} & -\frac{1}{T_A} & -\frac{k_A k_{vd}}{T_A} \\ k_7 & 0 & k_8 & 0 & -k_9 \end{bmatrix}$$

$$\begin{bmatrix} \Delta \delta \\ \Delta \omega \\ \Delta E_q' \\ \Delta E_{fd} \\ \Delta v_{dc} \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 \\ -\frac{k_{pe}}{M} & -\frac{k_{p\delta e}}{M} & -\frac{k_{pb}}{M} & -\frac{k_{p\delta b}}{M} \\ -\frac{k_{qe}}{T_{do}'} & -\frac{k_{q\delta e}}{T_{do}'} & -\frac{k_{qb}}{T_{do}'} & -\frac{k_{q\delta b}}{T_{do}'} \\ -\frac{k_A k_{ve}}{T_A} & -\frac{k_A k_{v\delta e}}{T_A} & -\frac{k_A k_{vb}}{T_A} & -\frac{k_A k_{v\delta b}}{T_A} \\ k_{ce} & k_{c\delta e} & k_{cb} & k_{c\delta b} \end{bmatrix}$$

$$\begin{bmatrix} \Delta m_E \\ \Delta \delta_E \\ \Delta m_B \\ \Delta \delta_B \end{bmatrix}$$

POWER SYSTEM STABILIZER

In this paper we compared performance of two controllers, i.e., power system stabilizer and Neuro-Fuzzy controller. Traditional method of damping LFO is by using Power System Stabilizer (PSS)

The basic function of PSS is to add damping to the generator rotor oscillations by controlling its excitation using auxiliary stabilizing signal.

PSS contains three important blocks phase-lead compensation block, signal washout block, exciter gain block phase-Lead block is used to damp rotor oscillations; the PSS must produce a component of electric torque in phase with rotor speed deviation. This requires phase-lead circuits to be used to compensate for the lag between the exciter input and the required electric torque. The required phase shift is provided by phase-lead block. Signal washout block serves as a high pass filter which allow signals associated with oscillations. So oscillations corresponds to large oscillations are not passed to PSS so that there is no negative damping torque. It allows PSS to respond only change in speed. Exciter gain block determines the amount of damping introduced by PSS. The gain should be set at a value corresponding to maximum damping.

HYBRID LEARNING PROCEDURE FOR ANFIS

For tuning Neuro Fuzzy controller we use hybrid learning procedure. Hybrid learning algorithm is combination of linear and nonlinear parameters learning algorithm this consists of Gradient decent method and least square estimate. Gradient decent method works as follows:

If a given training data contains P entries then error measure for p the entry of training data is given as sum of squared errors

$$\frac{\partial E_p}{\partial 0^L_{1,p}} = -2\left(T_{i,p} - 0^L_{1,p}\right)$$

where

#(L)= L th layer in adaptive network

$T_{m,p}$= mth component of pth target output vector

$O^L_{m,p}$ = mth component actual output vector

Then over all error is

$$E = \sum_{p=1}^{p} E_p$$

Then we calculate error rate $\partial E_p / \partial O$ for pth training data for each node output node O. The error rate for the output node at (L,i) can be calculated by

$$\frac{\partial E_p}{\partial O^L_{Lp}} = -2\left(T_{i,p} - O^L_{Lp}\right)$$

Now if α is a parameter of the given adaptive network then we can write

$$\frac{\partial E}{\partial \alpha} = \sum_{p=1}^{p} \frac{\partial E_p}{\partial \alpha}$$

Updating the formula for the generic parameters α is

$$\Delta\alpha = -\eta \frac{\partial E_p}{\partial \alpha}$$

Then for next iteration is

$$\alpha_{i+1} = \alpha_i + \Delta\alpha_i$$

where η is a learning rate can be further expressed as

$$\eta = \frac{k}{\sqrt{\sum_{\alpha} \frac{\partial E}{\partial \alpha}}}$$

Least square estimate works as follows, consider a single output function

Output = *F*(*I*, *S*)

where '*I*' is set of input variables and S is set of parameters. If there exists a function such that composite function HoF is linear in some elements of *S*. then these elements can be identified by least square method.

$S = S1 + S2$

Such that HoF is linear in *S*2.

For given values of S1 the Matrix equation is

$AX = B$

where X is unknown vector the least square estimate(LSE) of *X* is *X** can be calculated by

$X^* = (A^T A)^{-1} A^T B$

This problem cannot be used when $A^T A$ is non singular as a result we use a sequential formula to compute LSE. This is more efficient and can be easily modified to an on line version.

$$X_{i+1} = X_i + S_{i+1} a_{i+1} \left(b_{i+1}^T - a_{i+1}^T X_i \right)$$

$$S_{i+1} = S_i - \frac{S_{ia_{i+1}} a_{i+1}^T S_i}{1 + a_{i+1}^T S_i a_{i+1}} \quad i = 0, 1, ..., p-1$$

We can combine the gradient descent and least square estimate to update the parameters in an adaptive network.

Each cycle of this hybrid learning procedure is composed of a forward pass and a backward pass.

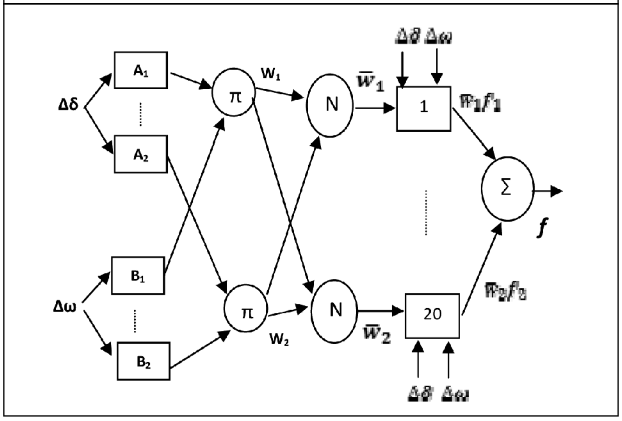
In the forward pass we supply input data and functional signals go forward until matrices A and B are obtained and the parameters in S2 are calculated by least squares formula.

In backward pass the errors rates are propagate from the output end towards the input end and parameters of in S1 are updated by gradient method.

NEURO-FUZZY CONTROLLER

Another controller is adaptive Neuro-fuzzy controller. The architecture of Neuro-Fuzzy controller was shown in Figure 2. In this section, we presented the procedure for designing adaptive Neuro-fuzzy controller with 2 inputs "$\Delta\delta$ and $\Delta\omega$ and one output that is f $\in$ {Δm_E, $\Delta\delta_E$, m_B, $\Delta\delta_B$ }. There are 20 membership functions and also 20 rules in the rules base for every input as shown in Figure 3. The figure gives structure of adaptive Neuro-fuzzy controller for a Sugeno fuzzy model with 2 inputs and 20 rules. A Hybrid algorithm was used to get parameters of Neuro-Fuzzy controller.

Figure 2: ANFIS Architecture for a Two-Input Sugeno Fuzzy Model with 20 Rules



Here Takagi and Sugeno fuzzy if then rules are used, so the output of each rule is a linear combination of input variable plus a constant term and finally the output is the weighted average of each rule's output. So we can write

If inputs of $\Delta\delta_i$ is A_i and $\Delta\omega$ is B_i then f_i=a_i”ä+b_i”ù+c_i

If μ_{A_i} and μ_{B_i} are the member ship functions of fuzzy sets A_i and B_i for i = 1, ..., 20. The output of Neuro-Fuzzy controller was explained below

Layer 1: This is an adaptive or square node which gives membership function output

Output = μ_{A_i} or μ_{B_i}

Layer 2: This layer is a circular node with π. It multiplies input and gives output

$$W_i = \mu_{A_i}(\Delta\delta),\ \mu_{B_i}(\Delta\omega), \qquad i = 1, .., 20$$

Layer 3: This layer is given by a circle with label N.

The output is ratio of i^{th} node firing strength to sum of all rules firing strength. Outputs are called as normalized firing strengths

$$\overline{w}_1 = \frac{w_1}{w_1 + \ldots + w_{20}}, \qquad 1 = 1, \ldots, 20$$

Layer 4: This is an adaptive node. The output of this layer is given by

$$f(\Delta\delta,\Delta\omega) = \frac{w_1(\Delta\delta,\Delta\omega) f_1(\Delta\delta,\Delta\omega) + \ldots + w_{20}(\Delta\delta,\Delta\omega) f_{20}}{w_1(\Delta\delta,\Delta\omega) + \ldots + w_{20}(\Delta\delta,\Delta\omega)}$$

Or leaving the arguments out

$$f = \frac{w_1 f_1 + \ldots + w_{20} f_{20}}{w_1 + \ldots + w_{20}}$$

Layer 5: Single layered node labeled " which calculates over all sum

$$f = \overline{w}_1 f_1 + \ldots + \overline{w}_{20} f_{20}$$

Figure 3: The Rule Surface

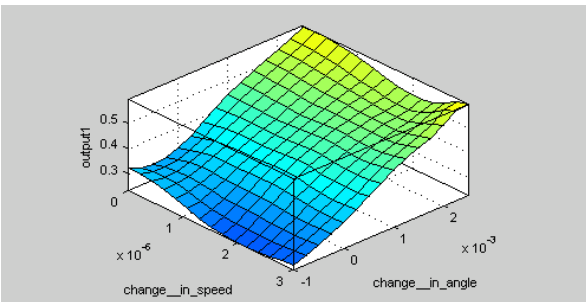


Figure 4: The Membership Function for Input Variable Δω

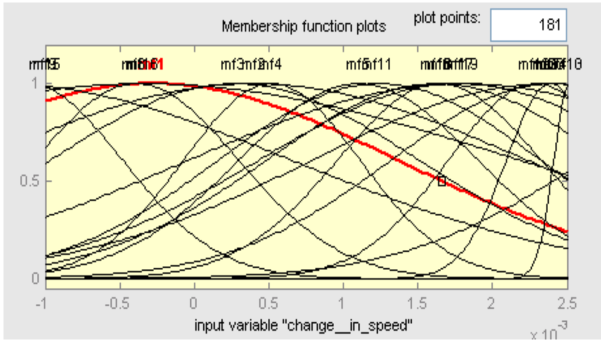
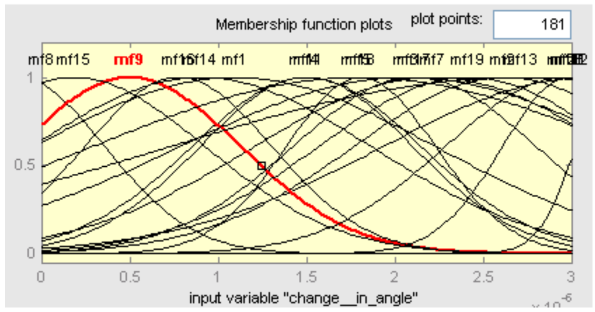


Figure 5: The Membership Function for Input Variable Δδ



SIMULATION RESULTS

In this paper two controllers were compared i.e. Neuro-Fuzzy and lead lag controller. In first

Figure 6: Angular Velocity Deviation During Step Change in Mechanical Input Power for Nominal Load (m_E Controller)

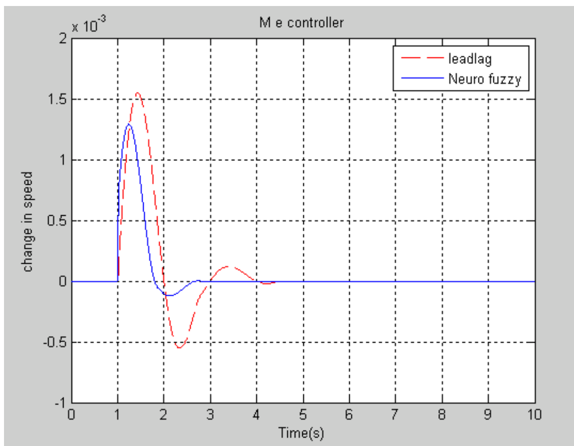


Figure 7: Angular Velocity Deviation During Step Change in Mechanical Input Power for Light Load (m_E Controller)

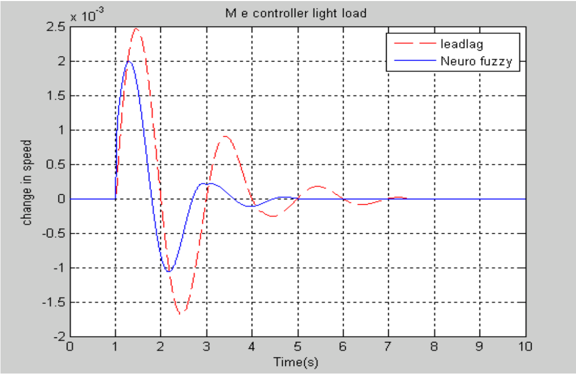


Figure 8: Angular Velocity Deviation During Step Change in Mechanical Input Power for Nominal Load (δ_E Controller)

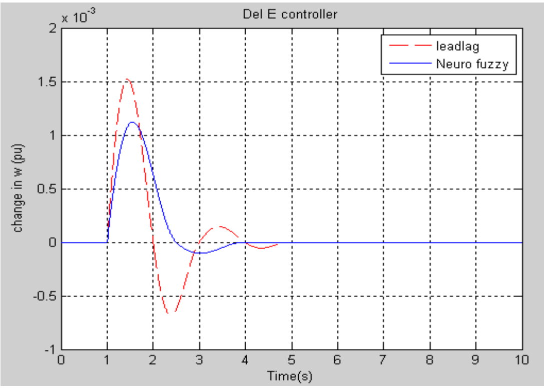


Figure 9: Angular Velocity Deviation During Step Change in Mechanical Input Power for Nominal Load (m_B Controller)

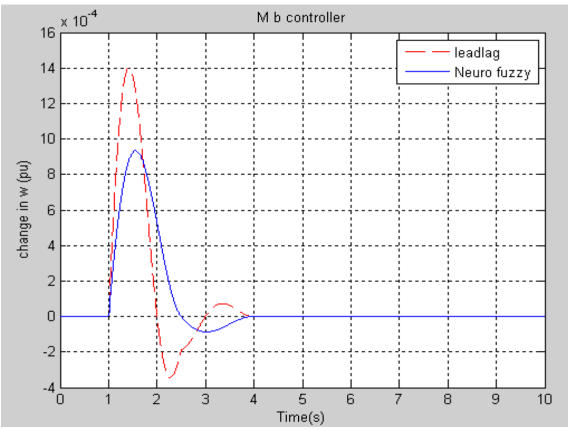


Figure 10: Angular Velocity Deviation During Step Change in Mechanical Input Power for Nominal Load (δ_B Controller)

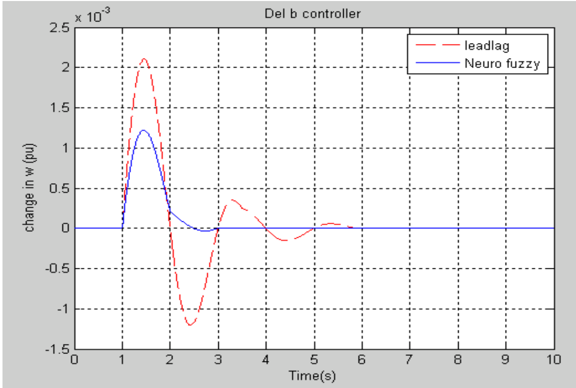
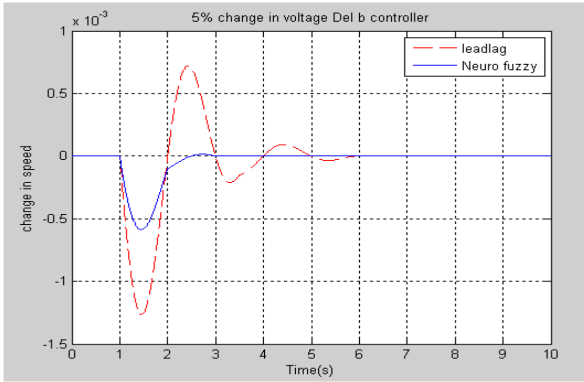


Figure 11: Response of Angular Velocity for 5% Step Change in Reference Voltage in the Case of Nominal Load (δ_E Controller)



four cases the speed deviation in $\Delta\omega$ is observed for 10% change in mechanical power at time of 1 sec. In last case is observed for 5% change in reference voltage when time is 1 s. And it is seen that Neuro-Fuzzy controller can decrease peak over shoot LFO quickly and also decreases the settling time.

Table 1 gives the settling time and peak over shoot of $\Delta\omega$ for different controllers. It is observed that optimum value of settling time and peak over shoot so it is preferred to damp LFO.

Table 1: Performance of Neuro-Fuzzy with Different Controllers

	Settling Time(s)		Peak Over Shoot	
	Lead-Lag	Neuro-fuzzy	Lead-Lag	Neuro-fuzzy
m_E= 0.4013	4.45	2.7	1.55*e-3	1.3*e-3
m_B= 0.0789	3.99	3.98	1.4*e-3	0.93*e-3
δ_E= –85.9478	4.98	3.95	1.52*e-3	1.12*e-3
δ_B= –72.2174	5.95	3	2.11*e-3	1.24*e-3

CONCLUSION

In this paper designing of adaptive neuro fuzzy controller was presented, which is used to damp LFO of a Single Machine Infinite Bus power system with UPFC. Here along with neuro fuzzy controller, a Lead- lag controller was designed. The simulation was performed for two controllers and for different kinds of faults. Comparison showed that the proposed adaptive neuro-fuzzy controller has good ability to reduce settling time and reduce amplitude of LFO. We can also use neural network ability such as adapting to changes, fault tolerance capability, recovery capability, High-speed processing because of parallel processing. We can also build a DSP chip with VLSI technology.

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APPENDIX

Generator:

$M = 2H = 8.0$ MJ/MVA, $D = 0.0$, $T'_{d0} = 5.044$ S

$X_d = 1.0$ pu, $X_q = 0.6$pu, $X'_d = 0.3$ pu

Exciter (IEEE Type ST1):

$K_A = 100$, $T_A = 0.001$S

Reactances:

$X_{lE} = 0.1$ pu, $X_E = X_B = 0.1$ pu, $X_{Bv} = 0.3$ pu, $X_e = 0.5$ pu

Operation Condition:

$P_e = 0.8$ pu, $V_t = 1$ pu, $V_t = 1$ pu

UPFC parameters: $m_E = 0.4013$, $m_B = 0.0789$, $\delta_E = -85.9478$,

$\delta_B = -72.2174$

DC Link: $V_{dc} = 2$ pu, $C_{dc} = 1$ pu