

## Enhancement of Transient Stability in A Multi-Machine Power System Using Adaptive Neuro-Fuzzy Controller for Facts Devices

**V.Sai Krishna Yadav**

PG Student,  
Department of EEE,  
St.Mark Educational Institution  
Society Group of Institutions  
Anantapuramu, AP, India.

**C.Hima Bindu**

Assistant Professor,  
Department of EEE,  
St.Mark Educational Institution  
Society Group of Institutions  
Anantapuramu, AP, India.

**M.Nagahimaja**

Assistant Professor & HoD  
Department of EEE,  
St.Mark Educational Institution  
Society Group of Institutions  
Anantapuramu, AP, India.

### **Abstract:**

*Long distance AC transmission is often subject to stability problems, which limits the transmission Capability which limits the transmission capability. Large interconnected power systems often suffer from weakly damped swings between synchronous generators and subsystems. This paper studies the comparative performance of SSSC and UPFC for the improvement of transient stability and damping of power swings of a multi-machine power system using Adaptive neuro-fuzzy controller. Simulation results are carried out in MATLAB/SIMULINK environment for multi-machine power system to analyse the effects of SSSC and UPFC on transient stability performance and damping of power swings of the system.*

**Index Terms:** Transient Stability, Power oscillation Damping, Adaptive Neuro-Fuzzy Inference System (ANFIS), SSSC, UPFC, Fuzzy Logic Controller (FLC).

### **INTRODUCTION**

This paper presents improvement of transient stability and power oscillation damping in a multi machine power system. Transient stability is the ability of the power system to maintain the synchronism after the sudden large disturbance. These disturbances may be because of the application of faults, clearing of faults, switching ON and OFF surges in EHV system. Methods to improve transient stability are use of breaking resistor, reduction in system transfer reactance, use of bundled conductors, short circuit

current limiters, and the placement of FACTS devices [2]. Power systems exhibit various modes of oscillation due to interactions among system components. Most of these oscillations are generally associated with transmission system disturbances and can occur due to step changes in load, sudden change of generator output, transmission line switching and short circuits. Depending on the characteristics of power systems, the oscillations may last for 3-20 seconds after a severe fault. Drawn out oscillations that last for a few seconds or more are usually the result of very light damping in the system and are pronounced at power transfers that approach the line's stability limit. During such angular oscillation period, significant cycle variations in voltages, currents, and transmission line flows will takes place. Therefore, it is important to damp out these oscillations as quickly as possible because they cause mechanical wear in power plants and many power quality problems.

In the past, power system stabilizers (PSSs) have been extensively used to increase the system damping for low frequency oscillations. The power utilities worldwide are currently implementing PSSs as effective excitation controllers to enhance the system stability. However, there have been problems experienced with PSSs over the years of operation. Some of these were due to the limited capability of PSS in damping only local and not inter area modes of oscillations. In addition, PSSs can cause great variations in the voltage profile under severe disturbances and they may even result in leading power factor operation and losing system stability.

Recently Flexible AC transmission systems (FACTS) have gained a great interest due to recent advances in power electronics. By using power electronics controllers a Flexible AC Transmission System offers greater control of power flow, secure operation and damping of power system oscillations. FACTS devices are used in power systems to improve both the steady state and dynamic performances of the systems. The voltage stability, steady state and transient stabilities of a complex power system can be improved by using FACTS devices. FACTS devices can control the various parameters of the power system such as voltage, phase angle and line impedance in a rapid and effective manner [3]. FACTS controllers can be divided into four categories: Series Controllers such as Thyristor Controlled Series Capacitor (TCSC), Thyristor Controlled Phase Angle Regulators (TCPAR), and Static Synchronous Series Compensator (SSSC); Shunt controllers such as Static Var Compensator (SVC), and Static Synchronous Compensator (STATCOM); combined series-series controllers such as Interline Power Controller (IPFC) and shunt series controllers such as UPFC (Unified Power Flow Controller).

In recent years, new artificial intelligence-based approaches have been proposed to design a FACTS-based supplementary damping controller. These approaches include genetic algorithm [4], particle swarm optimization [5], differential evolution [6], and multi-objective evolutionary algorithm [7]. Since 1989, artificial neural networks (ANN) methodology has captured the interest in a large number of applications in electrical power engineering [8]. The applications include economical load dispatching, power system stabilizers (PSS), etc., The artificial neural network controller based on fuzzy control (ANFIS controller) is applied for FACTS device. For the design purpose MATLAB/SIMULINK model of the power system with UPFC controller is developed. Simulation results are presented at different operating conditions and under various disturbances to show the effectiveness of the proposed controller. And the

results prove that the proposed UPFC-based ANFIS controller can improve transient stability and also can damp power oscillation more efficient than SSSC.

### POWER SYSTEM CONFIGURATION

The multi-machine power system with UPFC shown in Figure.1 is considered in this study. The system consists of three generators divided into two subsystems and are connected through an inter-tie. The generators are equipped with hydraulic turbine and governor (HTG) and excitation system. The HTG represents a nonlinear hydraulic turbine model, a PID governor system, and a servomotor. The excitation system consists of a voltage regulator and DC exciter, without the exciter's saturation function. Following a disturbance, the two subsystems swing against each other resulting in instability. To improve the stability the line is sectionalized and a UPFC is assumed on the mid-point of the tie-line. In Fig. 1, G1, G2 and G3 represent the generators; T/F1, T/F2 and T/F3 represent the transformers and L1, L2 and L3 represent the line sections respectively.

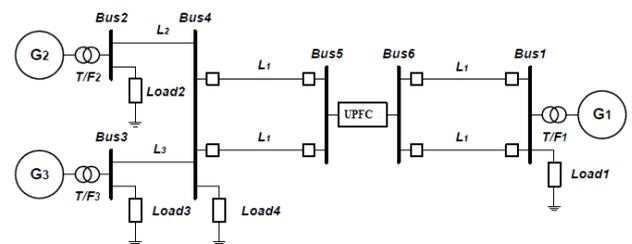


Figure 1: Three machine power system with UPFC

### OPERATING PRINCIPLES OF FACTS CONTROLLERS

#### A.Unified power flow controller (UPFC):

The unified power flow controller (UPFC) is the most versatile member of the Flexible AC Transmission Systems (FACTS) family using power electronics which can provide simultaneous control of power system parameters such as transmission voltage, line impedance and phase angle. The UPFC uses a combination of a shunt controller (STATCOM) and a series controller (SSSC) interconnected through a common DC bus as shown in Figure.2 As shown in the

figure, UPFC consist of two back to back converters named VSC1 and VSC2, which are operated from a DC link provided by a dc storage capacitor [3]. One of the two converters is connected in series with the transmission line through a series transformer and the other in parallel with the line through a shunt transformer. The dc side of the two converters is connected through a common capacitor, which provides dc voltage for the converter operation. The power balance between the series and shunt converters is a prerequisite to maintain a constant voltage across the dc capacitor. As the series branch of the UPFC injects a voltage of variable magnitude and phase angle, it can exchange real power with the transmission line and thus improves the power flow capability of the line as well as its transient stability limit. The shunt converter exchanges a current of controllable magnitude and power factor angle with the power system. It is normally controlled to balance the real power absorbed from or injected into the power system by the series converter plus the losses by value.

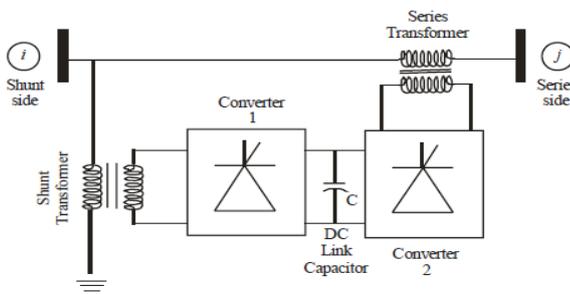


Figure 2: A block diagram of the UPFC scheme used in FACTS (single line diagram)

### B. Static Synchronous series compensator (SSSC):

A SSSC is a solid state voltage source converter, which operated as a controllable AC voltage source, and connected in series with transmission line and can operate, in both capacitive as well as inductive mode which makes effective in controlling power flow of the system. By varying the magnitude of injected voltage in quadrature with line current, the SSSC performs the function of variable reactance compensator, either capacitive or inductive [3]. The basic scheme of SSSC is as shown in Figure3. The variation of injected

voltage is performed by means of a Voltage-Sourced Converter (VSC) connected on the secondary side of a coupling transformer. The VSC uses forced – commutated power electronic devices (GTO'S IGBT'S or IGCT'S) to synthesize a voltage  $V_{conv}$  from a DC voltage source.

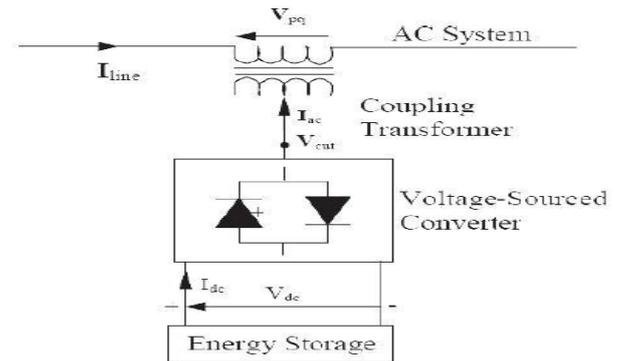


Figure 3: SSSC configuration

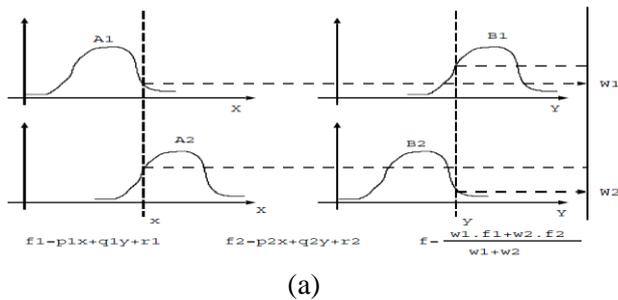
### ANFIS APPROACH

ANFIS uses a hybrid learning algorithm to identify parameters of Sugeno type fuzzy inference systems. It applies a combination of the least squares method and the back propagation gradient descent method for training fuzzy inference system membership function parameters to emulate a given training data set. ANFIS algorithm is composed of fuzzy logic and neural networks with 5 layers to implement different node functions to learn and tune parameters in a fuzzy inference system (FIS) structure using a hybrid learning mode. Parameters will be identified for membership function (MF) and FIS by repeating the forward and backward passes [9, 10]. In the forward pass of the hybrid learning algorithm, node outputs go forward until layer 4 and the consequent parameters are identified by the least-squares method. In the backward pass, the error signals propagate backwards and the premise parameters are updated by gradient descent.

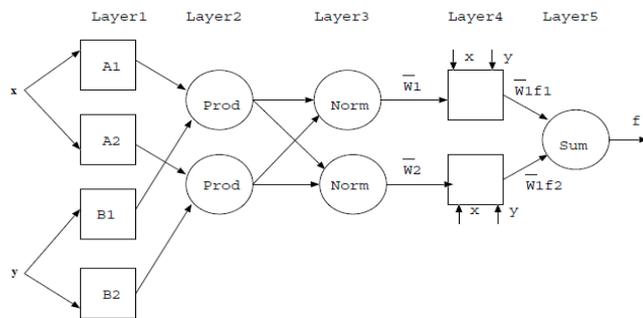
For simplicity, we assume that the examined fuzzy inference system has two inputs  $x$  and  $y$  and one output. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is defined as:

Rule 1: If x is  $A_1$  and y is  $B_1$ , then  $f_1 = p_1x + q_1y + r_1$ ;

Rule 2: If x is  $A_2$  and y is  $B_2$ , then  $f_2 = p_2x + q_2y + r_2$ ;



(a)



(b)

Figure 4: (a) A two inputs first order Takagi –Sugeno fuzzy model with two rules; (b) The equivalent ANFIS architecture.

where  $x$  and  $y$  are the inputs,  $A_i$  and  $B_i$  are the fuzzy sets,  $f_i$  are the outputs within the fuzzy region specified by the fuzzy rule,  $p_i$ ,  $q_i$  and  $r_i$  are the design parameters that are determined during the training process.

Different layers with their associated nodes are described below:

**Layer1.** Every node  $I$  in this layer is an adaptive node. Parameters in this layer are called premise parameters.

**Layer2.** Every node in this layer is a fixed node labeled  $\Pi$ , whose output is the product of all the incoming signals. Each node output represents the firing strength of a rule.

**Layer3.** Every node in this layer is a fixed node labeled  $N$ . The  $i$ th node calculates the ratio of the  $i$ th rules firing strength. Thus the outputs of this layer are called normalized firing strengths.

**Layer4.** Every node  $i$  in this layer is an adaptive node. Parameters in this layer are referred to as consequent parameters.

**Layer5.** The single node in this layer is a fixed node labelled  $\Sigma$ , which computes the overall output as the summation of all incoming signals.

The main benefit of the hybrid approach is that it converges much faster since it reduces the search space dimensions of the original pure back propagation method used in neural networks. The overall output can be expressed as a linear combination of the consequent parameters.

Table 1: Forward and backward pass for ANFIS

	Forward pass	Backward pass
Premise Parameters	Fixed	Gradient descent
Consequent Parameters	Least-squares estimator	Fixed
Signals	Node outputs	Error Signals

**A.Modeling of UPFC-based ANFIS controller:**

The proposed ANFIS controller utilizes Sugeno-type Fuzzy Inference System (FIS) controller, with the parameters inside the FIS decided by the neural-network back propagation method. The ANFIS controller is designed by taking speed deviation & acceleration as the inputs. The output stabilizing signal is computed using the fuzzy membership functions depending on the input variables. The effectiveness of the proposed approach to modelling and simulation of UPFC controller is implemented in Simulink environment of MATLAB. ANFIS-Editor is used for realizing the system and implementation.

In a conventional fuzzy approach the membership functions and the consequent models are fixed by the model designer according to a prior knowledge. If this set is not available but a set of input-output data is observed from the process, the components of a fuzzy system (membership and consequent models) can be represented in a parametric form and the parameters are tuned by neural networks. In that case the fuzzy systems turn into an ANFIS system. The FLC uses 49 rules and 7 membership functions in each variable to compute output and exhibits good performance. The rule-base is shown in Table. 2

**Table 2: Rule base for seven membership function**

Change In Error	Error						
	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	ZE
NM	NB	NB	NB	NM	NS	ZE	PS
NS	NB	NB	NM	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PM	PB	PB
PM	NS	ZE	PS	PM	PB	PB	PB
PB	ZE	PS	PM	PB	PB	PB	PB

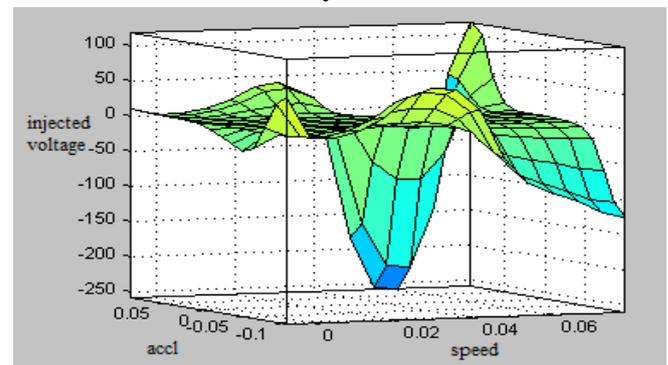
Now main aim is to extract a smaller set of rules using ANFIS learning and to do the same the following steps are followed:

**1) Data generation** - To design the FLC, some data is needed, i.e., a set of two-dimensional input vectors and the associated set of one-dimensional output vectors are required. Here, the training data has been generated by sampling input variables speed deviation & acceleration uniformly and computing the value of stabilized signal for each sampled point.

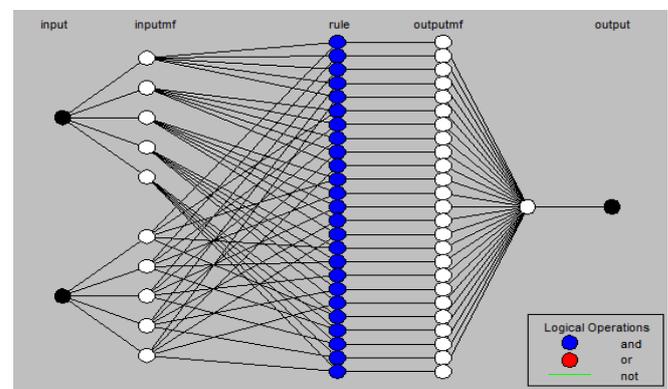
**2) Rule extraction and membership functions** – After generating the data, the next step is to estimate the initial rules. Then after applying Subtractive Clustering algorithm rules are extracted. These rules are not so close to the identified system. Hence, there is a need of optimization of these rules. Hybrid learning algorithm is used for training to modify the

above parameters after obtaining the Fuzzy inference system from subtracting clustering. This algorithm iteratively learns the parameter of the premise membership functions via back propagation and optimizes the parameters of the consequent equations via linear least-squares estimation. The training is continued until the error measure becomes constant.

**3) Results** -The ANFIS learning has been tested on a variety of linear and nonlinear processes. The objective here is to justify whether the ANFIS controller with less number of rules and membership functions can provide the same level of performance as that of the original one (system with 49 rules). To demonstrate the effectiveness of the proposed combination, the results are reported for system with 25 rules and system with optimized rule base. After reducing the rules the computation become fast and it also consumes less memory.



**Figure 5: Control Surface of UPFC-based Neuro-Fuzzy Controller**



**Figure 6: Structure of Sugeno type ANFIS with 25 rules for UPFC**

## SIMULATION RESULTS

The Sim Power Systems (SPS) toolbox is used in the present study for all simulations and UPFC-based neuro-fuzzy controller design [11]. The SPS's main library, "powerlib", contains three phase-models of typical power equipments such as machines, governors, excitation systems, transformers, lines, and FACTS devices.

The Powergui block is necessary for simulation of any Simulink model containing Sim Power systems blocks. It provides useful graphical user interface (GUI) tools for the analysis of SPS models. The library also contains the Powergui block that opens a GUI for the steady-state analysis of electrical circuits. It performs load flows and initializes the three-phase networks containing three-phase machines so that the simulation starts in steady state.

In order to optimally tune the parameters of the UPFC based neuro-fuzzy controller, as well as to assess its performance and robustness under wide range of operating conditions with various fault disturbances and fault clearing sequences, the test system depicted in Figure 1 is considered for analysis. The MATLAB/Simulink model of the example power system is developed using SPS block-set as shown in Figure 6. The ratings of the generators are taken as 2100MVA each (G2 and G3) in one subsystem and 4200MVA (G1) in the other subsystem. The generators with output voltages of 13.8KV are connected to an inter-tie through 3-phase step up transformers. All of the relevant parameters are given in the Appendix.

A three-cycle, three-phase fault is applied at one of the line sections between Bus 1 and Bus 6, near Bus 6, at  $t = 1$  sec. The fault is cleared by opening the faulty line, and the line is reclosed after three cycles.

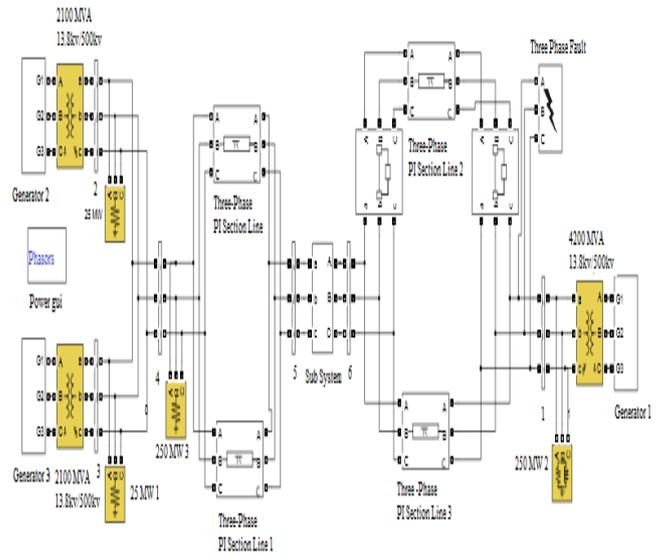


Figure 7 : MATLAB/Simulink Model of a Three Machine Power System Equipped with UPFC with Fault at bus 1

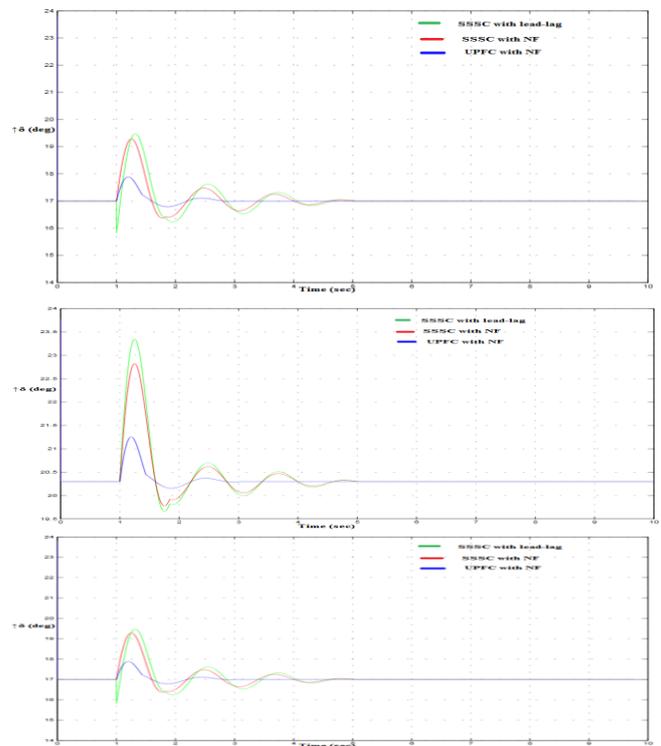


Figure 8: Variation of Inter-Area Modes of Oscillations against Time for Lead-Lag, SSSC and UPFC for Three-Cycle unbalanced faults at Bus 1: (a) L-G fault; (b) L-L faults; (c) L-L-G fault.

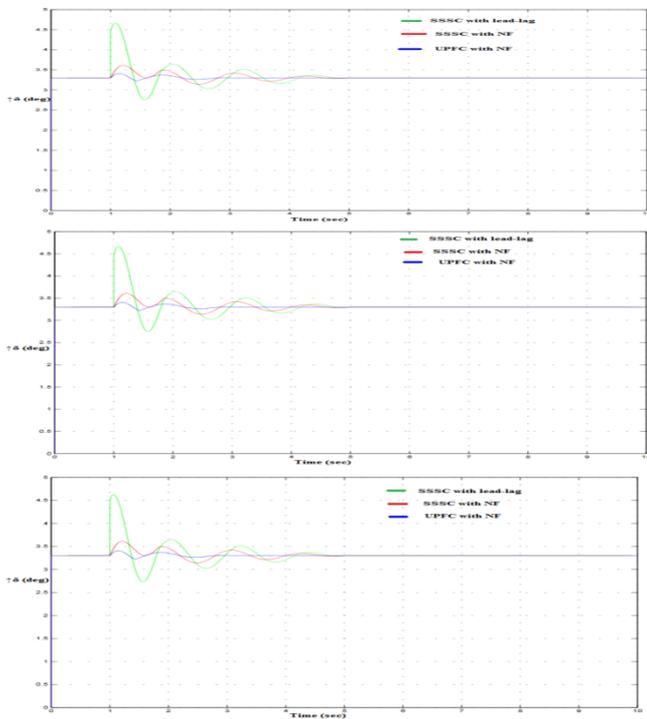


Figure 9: Variation of Local Modes of Oscillations against time for Lead-Lag, SSSC and UPFC for three cycle unbalanced faults at Bus 1: (a) L-G fault; (b) L-L faults; (c) L-L-G fault.

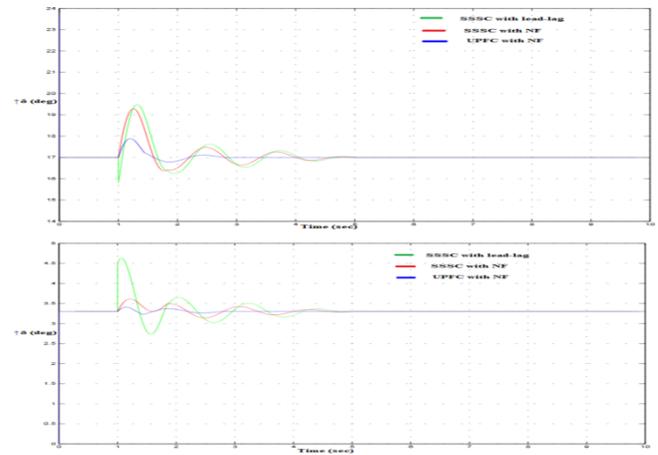


Fig.11: Variation of Local Modes of Oscillations (between G2 and G3) against Time for a Three-Cycle, Three Phase Fault near bus 6.

### CONCLUSION

In this paper, Transient Stability improvement and Power Oscillation damping of a three machine power system by various FACTS devices such as SSSC and UPFC is analysed. It is clear from the simulation results that there is a considerable improvement in the system performance with the presence of UPFC for which the settling time and amplitude of LFO is reduced when compared to SSSC and lead-lag, which shows that the proposed UPFC-based neuro-fuzzy controller provides efficient damping to power system oscillations and greatly improves the system voltage profile.

### APPENDIX

**System data: All data are in p.u. unless specified otherwise**

#### Generators

Nominal powers:  $S_{B1} = 4200$  MVA,  $S_{B2}=S_{B3}= 2100$  MVA,

Nominal voltage:  $V_B=13.8$  KV, Nominal frequency:  $f = 60$  Hz,

Stator resistance:  $R_s=0.0028544$ ,

Reactance's:  $X_d = 1.305$ ,  $X'_d = 0.296$ ,  $X''_d = 0.252$ ,  
 $X_q = 0.474$ ,  $X'_q = 0.243$ ,

$X''_q = 0.18$ , Time constants:  $T_d = 1.01s$ ,  $T = 0.053s$ ,  
 $T''_{q0} = 0.1s$ ,

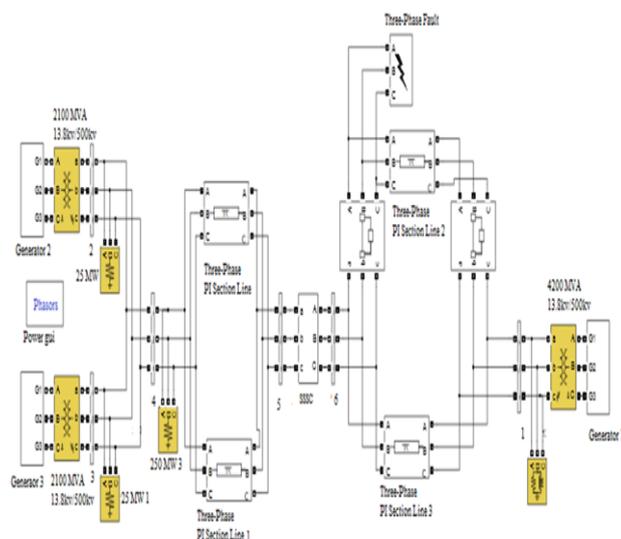


Figure 10: MATLAB/SIMULINK Model of three machine power System Equipped with UPFC & fault at bus 6

Coefficient of inertia and pair of poles:  $H = 3.7s$ ,  $p = 32$

### Excitation Systems

Low-pass filter time constant:  $T_{LP} = 0.02 s$ ,  
Regulator gains and time constants:  $K_A = 200$ ,  $T_A = 0.001 s$   
Exciter gains and time constants:  $K_e = 1$ ,  $T_e = 0$ ,  
Transient gain reduction:  $T_b = 0$ ,  $T_c = 0$   
Damping filter gains and time constants:  $K_f = 0.001$ ,  
 $T_f = 0.1 s$ ,  
Regulator output limits and gains:  $E_{fmin} = 0$ ,  $E_{fmax} = 7$ ,  
 $K_p = 0$

### Hydraulic Turbine and Governor

Servo-motor gains and time constants:  $K_a = 3.33$ ,  $T_a = 0.07$   
Gate opening limits:  $G_{min} = 0.01$ ,  $G_{max} = 0.97518$ ,  
 $V_{gmin} = -0.1 p.u./s$ ,  $V_{gmax} = 0.1 p.u./s$   
Permanent droops:  $R_p = 0.05$ , PID regulators:  $K_p = 1.163$ ,  $K_i = 0.105$ ,  $K_d = 0$ ,  
 $T_d = 0.01 s$  Hydraulic turbines:  $\beta = 0$ ,  $T_w = 2.67 s$

### Transformers

Nominal powers:  $S_{B1} = 4200 MVA$ ,  $S_{B2} = S_{B3} = 2100 MVA$ ,  
Winding connections:  $D_1/Y_g$   
Winding parameters:  $V_1 = 13.8 kV$ ,  $V_2 = 500 kV$ ,  $R_1 = R_2 = 0.002$ ,  $L_1 = 0$ ,  $L_2 = 0.12$ ,  
Magnetization resistance:  $R_m = 500$ , Magnetization reactance:  $L_m = 500$

### Transmission lines

Number of phases: 3-Ph, Resistance per unit length:  $R_1 = 0.02546 \Omega/km$ ,  
 $R_0 = 0.3864 \Omega/km$  Inductance per unit length:  $L_1 = 0.9337 \times 10^{-3} H/km$ ,  
 $L_0 = 4.1264 \times 10^{-3} H/km$ ,  
Capacitance per unit length:  $C_1 = 12.74 \times 10^{-9} F/km$ ,  
 $C_0 = 7.751 \times 10^{-9} F/km$ ,  
Line lengths:  $L_1 = 175 km$ ,  $L_2 = 50 km$ ,  $L_3 = 100 km$ .

### UPFC

Converter rating:  $S_{nom} = 100 MVA$ , System nominal voltage:  $V_{nom} = 500KV$ ,  
Frequency:  $f = 60 Hz$ , Reference active and reactive power [ $P_{ref} Q_{ref}$ ] (pu): [5.87 -0.27]  
Maximum rate of change for references  $P_{ref} Q_{ref}$  (pu/s): 1  
Power regulator gains:  $K_p = 0.025$ ,  $K_i = 1.5$

### Loads

$Load_1 = 7500MW + 1500MVAR$ ,  $Load_2 = Load_3 = 25MW$ ,  $Load_4 = 250MW$

### REFERENCES

- [1]. Swasti R. Khuntia, "Simulation Study of a SSSC-based Neuro-Fuzzy Controller for Improvement of Transient Stability in a Three-Machine Power System". Published in Energy tech, 2012 IEEE.
- [2]. P. Kundur, "Power System Stability and Control", McGraw-Hill, 1994.
- [3]. N.G. Hingorani and L. Gyugyi. "Understanding FACTS: Concepts and technology of flexible AC transmission systems" IEEE Press, New York 2000.
- [4]. S. Panda, and N. P. Padhy, "Comparison of particle swarm optimization and genetic algorithm for FACTS-based controller design", Appl. Soft Computing., vol.8, no.4, pp. 1418-1427, 2008.
- [5]. S. Panda, N. P. Padhy, and R. N. Patel, "Power system stability improvement by PSO optimized SSSC based damping controller", Electrical. Power Comp. Syst., vol. 36, no.5, pp. 468-490, 2008.
- [6]. S. Panda, "Differential evolutionary algorithm for TCSC-based controller design", Simulation. Model. Practical. Theory, vol.17, no. 10, pp. 1618-1634, 2009.



[7].S. Panda, “Multi-objective evolutionary algorithm for SSSC-based controller design”, Electrical. Power System. vol. 79, no. 6, pp. 937-944, 2009.

[8].J. R. Jang, “ANFIS: Adaptive-network-Based Fuzzy Inference System”, IEEE Trans. Systems Cybernetics, vol. 23, no.3, pp. 665-685, May 1993.

[9].M. Ansarian, G. H. Shakouri, J. Nazarzadeh, and S. M. Sadeghzadeh, “A novel neuro-optimal approach for LFC decentralized design in multi area power system”, Power and Energy Conference, 2006.

[10].M. Z. Youssef, P. K. Jain, and E. A. Mohamed, “A robust system stabilizer configuration using artificial neural network based on linear optimal control”, IEEE CCECE 2003 , vol.1, pp. 569- 573, May 2003.

[11].Sim Power System’s 4.3 users guide, Available at <http://www.mathworks.com/products/simpower>.