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# Coordinated Design and Comparison of Adaptive Power System and Controller Output Error Method

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***ABSTRACT***
*This article describes how to improve the stability of a multimachine power system by simultaneously adjusting the PSS and static VAR compensator parameters with a Particle Swarm Optimized NeuroFuzzy controller. The controller works to enhance the dampening of the rotor speed deviations of its nearby generators by providing a reference voltage signal for the PSS & SVC. The field of intelligent control involves creating control algorithms by modeling specific traits of intelligent biological systems. The controller is trained offline by PSO and simulation results that describe the performance of the NeuroFuzzy controller are provided in order to provide nonlinear optimum control during abnormal operating circumstances of the power systems.*

***Keywords*: *adaptive power systems, error method, controller***

## I. INTRODUCTION

To design more flexible controller, systems are integrated with other elements, such as logic, reasoning and heuristics into the more algorithmic techniques provided by conventional control theory and such systems have come to be known as intelligent control systems. Now a day, to control nonlinear dynamic complex problems Fuzzy systems are widely used. The optimization based intelligent techniques can be used to identify the nonlinear systems and controller parameters in presence of uncertainty, noise [1, 2]. Compared to fixed parameters of linear controller, Fuzzy controller behaves by changing its gain in nonlinear circumstances. It maps crisp inputs to fuzzy values, and convert fuzzy values in to crisp output by fuzzification and defuzzification techniques. To design efficient fuzzy logic controller selection of proper membership function is a critical one. However, it has been shown that altering the fuzzy controller parameters plays a dominant effect in the performance of the system [3]. Several methods have been proposed to update the fuzzy rule base to respond to the changes in the system dynamics [4]. Clearly, this scheme suffers due to improper selection of fuzzy controller parameters. Therefore it is essential to integrate neural network to learn system dynamics, acquire knowledge and combined with fuzzy logic for decision making.

The focus of this paper is to design optimal neural-network-based fuzzy (NeuroFuzzy) controller by optimally adjusting its antecedent and consequent (output) parameters. The connectionist systems theory can be applied to the complexity and the dynamics of many real-world engineering problems for decision making and control, the systems can adaptively update the controller parameters in on-line. [5], [6], [7].The Connectionist Systems are neural network systems that establish their structure, functionality and interior model through continuous online/ offline learning from the nonlinear complex dynamic systems. To show the superiority of optimal adaptive NeuroFuzzy logic controllers, specific control application is deliberately preferred in this paper since the selected system characterizes a nonlinear dynamic system with parameter uncertainties and mathematical model cannot be attained easily. The design of nonlinear controllers is not easy due to unavailability of exact model for the system. Several researchers have proposed Fuzzy logic [8], Neural networks [9] or NeuroFuzzy systems [10] for designing controllers for the FACTS devices.

The paper is organized as follows. Section II summarizes the modeling of the multimachine power system with SVC & PSS. The structure of the proposed SVC NeuroFuzzy external controller is explained in Section III. Section IV provides the details of the training process required for the proposed controller. Simulation results are provided in Section V. Finally, the concluding remarks are given in Section VI.

## II. SYSTEM MODEL

The study system consists of 4 machines, two static load and an interconnecting network including transformers and transmission lines. The excitation system for the synchronous generator is the IEEE TYPE 1 excitation system with constant prime mover mechanical torque.

### 2.1. Synchronous Generators

The synchronous generator model used for dynamic analysis is the two axis model with four state variables [11].

$$\dot{E'}_{di} = \frac{1}{\tau'_{qoi}}(-E'_{di} - (x_{qi} - x'_{qi})I_{qi}$$

$$\dot{E'}_{qi} = \frac{1}{\tau'_{doi}}(-E'_{FDi} - E'_{qi} + (x_{di} - x'_{di})I_{di}$$

$$\dot{\omega}_i = \frac{1}{\tau_{ji}}(T_{mi} - D\omega_i - T_{ei})$$

$$\dot{\delta} = \omega_i$$

Where the state variables are $E'_d$ is the direct axis component of voltage behind transient reactance $E'_q$ is the quadrature axis component of voltage behind transient reactance, ω is the angular velocity of rotor, δ is rotor angle. The generic power system stabilizer (PSS) block can be used to add damping to the rotor oscillations of the synchronous machine by controlling its excitation. The generic power system stabilizer is modeled by the nonlinear system as shown in Fig. 2 .The conventional lead-lag PSS as shown in Fig. 1 [12].

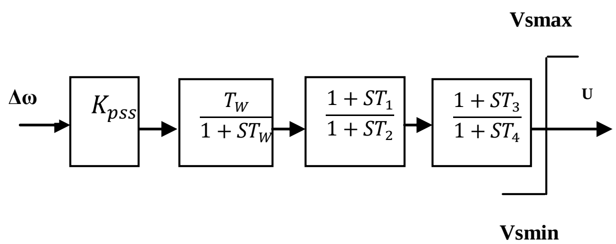


**Figure 1:** .Conventional lead-lag PSS

$T_W$ is the time constant of wash out circuit, PSS gain $K_{pss}$ ,time constants $T_1, T_2, T_3, T_4$ are determined in offline by optimization algorithm, and adaptively adjusted by neurofuzzy controller.

### 2.2 Static Var Compensators

SVC is a shunt connected variable impedance type FACTS controller whose output is adjusted to exchange capacitive or inductive current so as to control specific power system variables. The configuration of SVC is shown if Fig.2. The damping of Power system oscillations is implemented by employing two lead lag controllers to provide control signals to SVC. The following equation is the transfer function of SVC lead lag controller

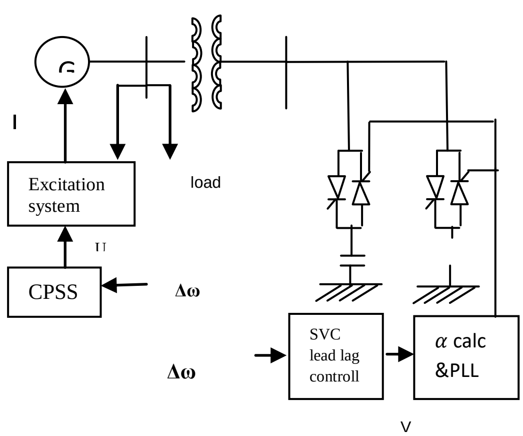


**Figure 2:** Configuration of SVC

These parameters are adaptively adjusted by Fuzzy Controller. When the SVC is operating in voltage regulation mode, its response speed to a change of system speed depends on the parameters of lead lag controller.

## III. ADAPTIVE NEUROFUZZY CONTROLLER

The Adaptive Neuro Fuzzy Inference System is a type III (Takagi-Sugeno type )fuzzy system applied to automate the design of Fuzzy Controller. Automation of controller is done by tuning Right Hand Side of if then rule by implementing the TSK controller in the network and tuning left hand side of if then rule by back propagation algorithm of neural networks. It is a network-type structure which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map. ANFIS integrates the best features of fuzzy system and neural networks. To emulate a given training data set, ANFIS combines least-squares method and the back propagation gradient descent method for training FIS membership function parameters. ANFIS network has nodes and directional links in which each node is assigned to perform a particular function on the incoming signals and pass it through the links by indicating the direction. All computations can be explained in a diagram form. ANFIS normally has 5 layers of neurons in which neurons in the same layer are of the same functional family.

**Layer 1: Fuzzification Layer**

Each node generates the membership grades of a linguistic input variable $\Delta\omega$ and derivative of $\Delta\omega$.The premise parameters A1 to A5 and B1 to B5 membership values can be trained using the hybrid learning algorithm. This membership function is given by equation (3.1).The generalized bell function depends on three parameters a, b, c as given by

$$F(x;a,b,c)=\frac{1}{1+\left(\left(\frac{|x-c|}{|a|}\right)^{2b}\right)} \qquad (3.1)$$

Where the parameter *b* is usually positive. The parameter *c* locates the center of the curve. The shape of the bell-shaped function depends upon premise parameters such as a, b ,c.. Parameters in that layer are called premise parameters.

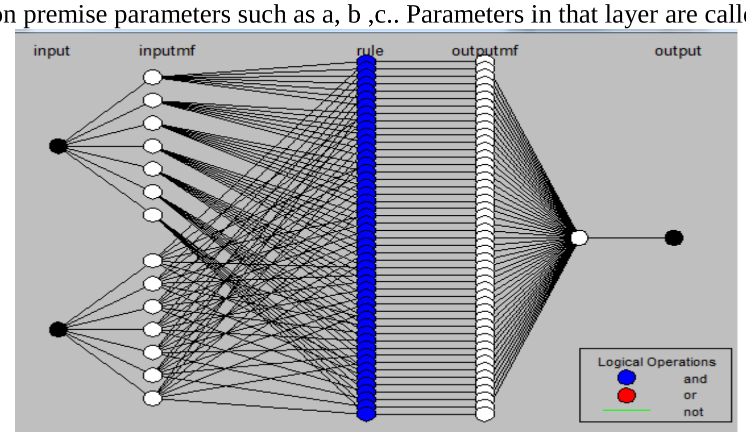


**Figure 3:** Structure of the Adaptive Neuro Fuzzy Inference System

**Layer 2: Firing Strength layer**

Fuzzy inferencing is done with nodes of layer2 using multiplication operator. The number of all possible antecedent combination is 49. In general, any other fuzzy AND operation can be used. At this node output is a product of all incoming signals.The output of ith node of layer 2 is specified by equation (3.2) as:

$$O_i^2=\omega_i=\min(\mu_{Ai}(x), \mu_{Ai}(y)) \qquad (3.2)$$

Where x, y represents the input linguistic variable.

**Layer 3: Normalization layer**

The Normalized firing strength of each rule is the ratio of the $i^{th}$ rule's firing strength to the sum of all rules firing strengths. Nodes in this layer are also fixed nodes. The output of $i^{th}$ node of layer 3 is given by equation (3.3) as:

$O_i^3 = \overline{\omega_i} = \frac{\omega_i}{\sum_{i=0}^{n} \omega_i}$; i =1, …. , 49, (3.3)

Where N is the no. of rules.

**Layer 4: Defuzzification Layer**

The output of each adaptive node is simply the product of the normalized firing strength and individual rule output of a corresponding rule ($r_i$) which is also known as consequence parameters. The output of $i^{th}$ node of layer 4 is given by equation (3.4) as:

$O_i^4 = \overline{\omega_i}\, r_i = \frac{\omega_i}{\sum_{i=0}^{n} \omega_i} r_i$; i =1,...49, (3.4)

where N is the no. of rules.

**Layer 5: Summing Layer**

This layer has only one that performs the function of a simple summer. This neuron calculates the sum of the outputs of all defuzzificated neurons and produces the overall ANFIS output. The output of layer 5 is given by equation (3.5) as:

$O_i^5 = U = \sum_{i=1}^{N} \overline{\omega_i}\, r_i$ (3.5)

## IV. TRAINING THE NEUROFUZZY CONTROLLER BY PSO ALGORITHM

To solve a particular problem, the training method plays an important role in determining the final performance of the ANFIS network. In this regard, several ANFIS training methods have been proposed in the literature. For instance, Jang [13] proposed a hybrid learning rule which combines the gradient descent technique and the least square estimator (LSE) method. Lin [14] combined the GA and the LSE in a hybrid method to optimize the ANFIS parameters. Lutfy et al. [15] used the GA to train all of the ANFIS parameters acting as a feedback controller to control nonlinear systems. Despite the fact that both the GA and the PSO methods have several similarities, PSO does not have complicated evolutionary operators such as the crossover and the mutation in the GA. Therefore, the computational complexity is less in the PSO technique than the GA, and this will make the PSO more suitable for the ANFIS training task, as will be seen in the comparative study presented in the results and discussion section of this work. Ghomsheh et al. [16] used the PSO with some modifications, which are inspired by natural evolutions, to train the ANFIS structure.

The PSO technique is one of the modern population based stochastic optimization technique, which was first introduced by Kennedy and Eberhart, in 1995. Using this technique, high-quality solution within shorter calculation time and stable convergence characteristic can be achieved and compared to other stochastic methods . A random potential solution, called particles, flies through different velocities through the problem space and achieves the optimal values. The Pbest is called as a personal best particle that keeps track of its coordinates in the solution space and associates with the best solution (fitness). The gbest is called as the global best value obtained so far by any particle in the neighborhood of that particle that is tracked by the PSO. Training is done off line and the cost function is based on the minimization of the error between actual and approximated output. Therefore, the goal of the design problem is minimizing Overshoot, undershoot, rise time and settling time of speed deviation signal.For this purpose, Integral of Time multiplied Absolute Error (ITAE) performance index is used [17-18] that contains all the specifications.

Min $F = \int_{t1}^{t2} t|\Delta\omega(t)|\, dt$

Where t1 and t2 are the study time limits and $\Delta\omega(t)$ represents the speed deviation of the generator.

**Step 1**

The PSO parameters weighting function, weighting factors c1, c2, population size and population with upper and lower bounds, the velocities for the pbests, gbest and the maximum number of iterations are initialized.

**Step 2**

Evaluate the objective function for each individual in the population

**Step 3**

Each individual's fitness function is compared with its pbest. The best fitness function among the pbests is denoted.

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**Step 4**

The velocity of each individual is modified. The modification of the particle's position can be mathematically modeled according the following equation

Vik+1 = wVik +c1 rand1(…) x (pbesti-sik) + c2 rand2(…) x (gbest-sik) ….. (1)
where,

vik : velocity of agent i at iteration k, weighting function,
cj : weighting factor, uniformly distributed random number between 0 and 1,
sik : current position of agent i at iteration k,
pbesti : pbest of agent i, gbest: gbest of the group.
w=wMax-[(wMax-wMin)xiter]/maxIter (2)

where

wMax= initial weight,
wMin = final weight,
maxIter = maximum iteration number,
iter = current iteration number.

sik+1 = sik + Vik+1

The schematic diagram of the system is shown in Fig. 4.It consists of the multimachine power system in Fig. 5, the SVC, and the controller. The input to the plant is the auxiliary voltage $V_a$ for SVC and U for Power system stabilizer generated by Adaptive NeuroFuzzy controller,and its output is the vector of the speed deviations of generators 1 and 2. The objective function is calculated and the controller parameters are optimized online to minimize the objective function.
Then NeuroFuzzy controller is tuned the parameters of SVC lead lag controller & Conventional Power System Stabilizer.

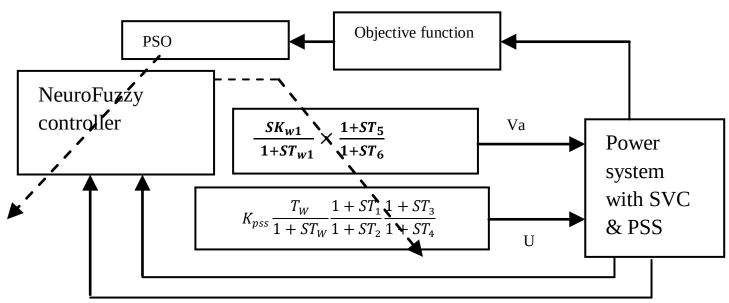



**Figure 4:** Schematic Diagram of the SVC & PSS Neurofuzzy External Controller

## V. SIMULATION RESULTS

To validate the proposed method, the simulations are carried out multi-machine power system in MATLAB software. Now the performance of the proposed coordinated method is studied for a multi-machine system shown in Figure 5 with a SVC and the parameters of this two-area system are given in [19].

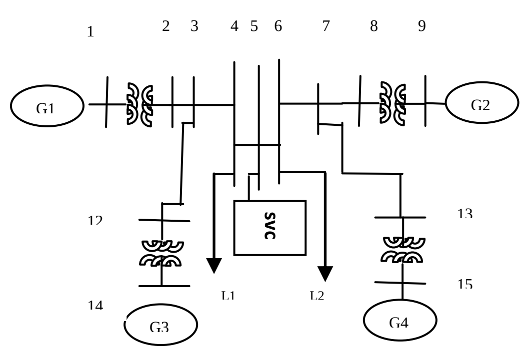



**Figure 5:** Two-Area 4 Machine Power System [19] with SVC & PSS

**Case(i):** In Conventional power system stabilizer the parameters are designed based on linear control techniques suitable for power system operates around an equilibrium point. The Power system is a nonlinear system, therefore PSS design is not suitable during critical faults. Fig.6. a, b, c clearly demonstrates the results.

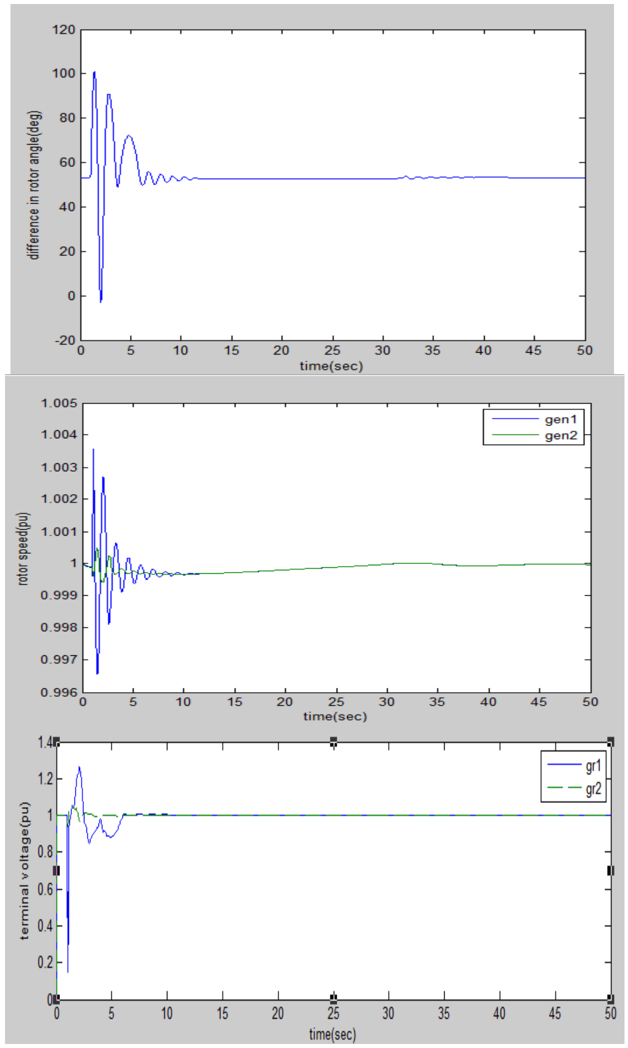



**Figure 6:** a)Difference of Rotor Angle b) Rotor Speed c) Terminal Voltage of Two Machines 3 Phase Fault at Line 3-4 (with PSS/without svc)

From the results it is evident that the design of PSS stabilizer produces oscillations during major disturbances.

**Case(ii):** Rotor angle deviations of synchronous generators with conventional PSS/With SVC

Fig.7. a, b, c shows the simulation results of power system with conventional PSS and SVC. The SVC operates at voltage control mode and the reference voltage is set at 1 Pu, then SVC controller is tuned, but the system still experiences a small magnitude of the oscillations.

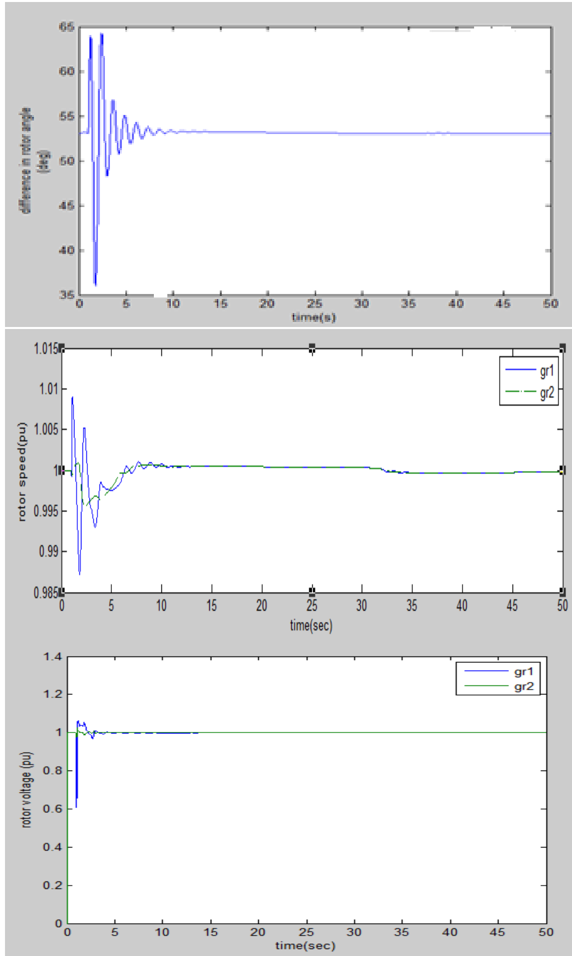
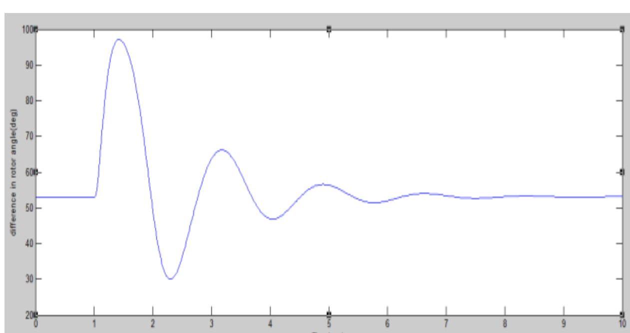



**Figure 7:** a)Difference of Rotor Angle b) Rotor Speed c) Terminal Voltage of Two Machines 3 Phase Fault At Line 3-4(With PSS/Withsvc)

The SVC operates in an external voltage control mode and the reference voltage is set by a controller that accepts difference in rotor angle as input, then SVC controller is tuned, but the magnitude of voltage oscillations is reduced, but still has oscillations in rotor speed. The SVC controller with speed deviation as input signal modifies the midpoint voltage as oscillation occurs. Terminal voltage is maintained at 1 PU, still experiences oscillations, if uncontrolled leads to an unstable system. Therefore the design SVC controller and PSS stabilizer by conventional method produces unsatisfied results. A Therefore nonlinear technique is adopted for controller design of damping oscillations.

Case(iii): ANN based Fuzzy controller for PSS:



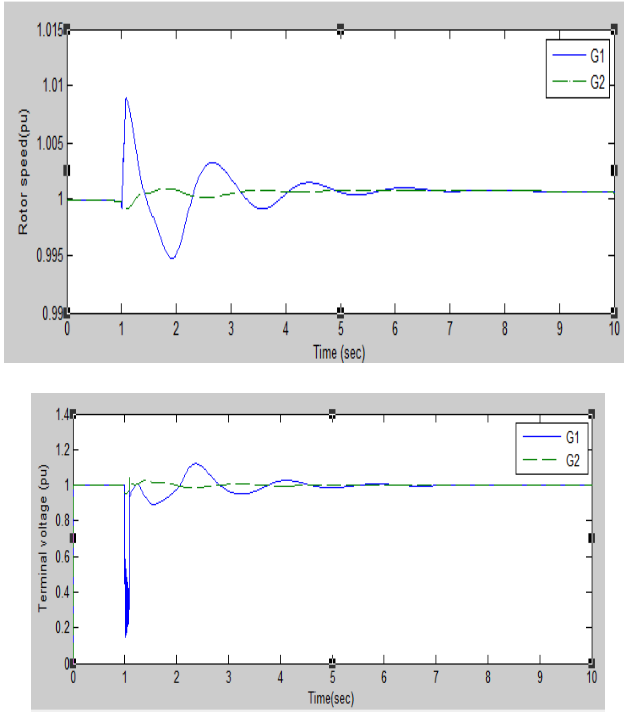
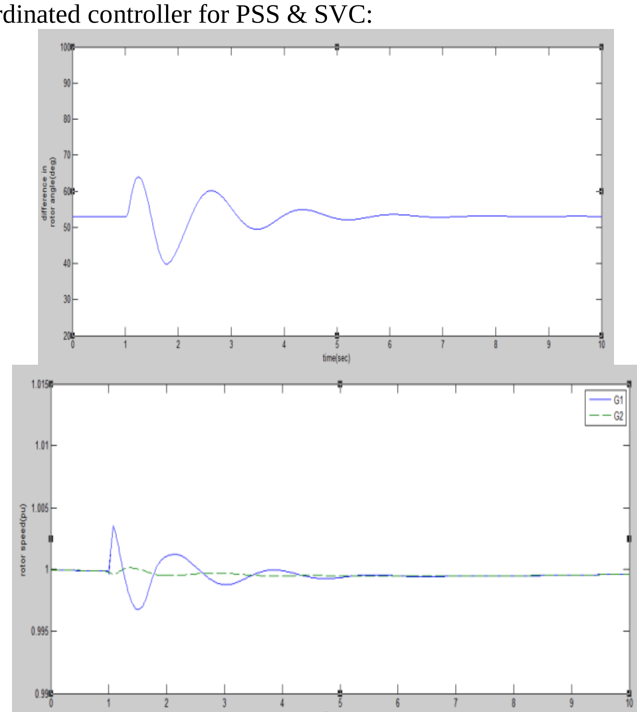



**Figure 8:** Design of PSS by ANN Based Fuzzy Inference System for 3 Phase Fault
a)Difference of Rotor Angle b) Rotor Speed c) Terminal Voltage of Two Machines 3 Phase Fault at Line 3-4(with PSS Only)

The Fig.8 a, b, c shows the results of ANN based design of power system stabilizer. The design of power system stabilizer enhances the voltage of G1 before 5 Sec, and oscillations are same as the design of conventional controller techniques. However ANN design improves the voltage stability, also provide superior performance during dynamic states of the power systems, but the design requires coordinated tuning of SVC and PSS for dynamic stability enhancement.

**Case(iv):** ANN based Fuzzy coordinated controller for PSS & SVC:



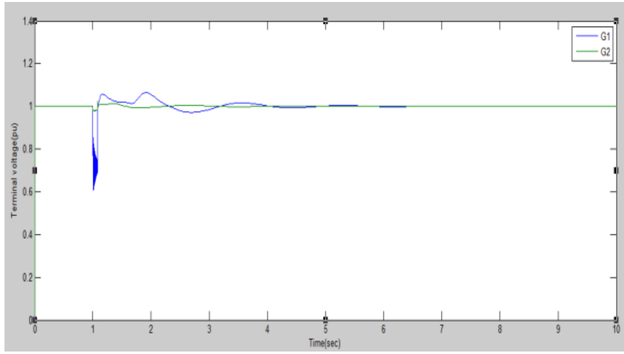



**Figure 9:** Design of Coordinated PSS & SVC Controller by ANN based Fuzzy Inference System for Three Phase Fault on Line 3-4 for 10 msec

a) Difference of Rotor angle b) Rotor Speed c) Terminal Voltage of Two Machines 3 Phase Fault at Line 3-4

The Fig 9 a, b, c shows the simulation results of the coordinated ANN based design of PSS, and SVC .The graph shows the best performance that can be obtained by intelligence technique. The intelligent based controller can tune the SVC and PSS controllerto obtain the superior performance in dynamic disturbances.

The designed controller parameters are as follows:

Number of nodes: 131
Number of linear parameters: 49
Number of nonlinear parameters: 42
Total number of parameters: 91
Number of training data pairs: 985
Number of fuzzy rules: 49

| Configuration | $\|d\theta\|$ (rad) | $\|\omega_1\|$ (pu) | $\|\omega_2\|$ (pu) | Volt Dip at G1 (pu) | $V_2$ (pu) |
|---|---|---|---|---|---|
| With PSS | 0.8547 | 1.004 | 1.001 | 0.2 | 1 |
| With PSS/SVC | 0.8540 | 1.003 | | 0.6 | 1 |
| Anfis PSS | 0.314 | 1.01 | 1.001 | 0.2 | 1 |
| Coordinated PSS/SVC anfis controller(3 phase fault) | 0.2791 | 1.01 | 0.995 | 0.6 | 1 |

**Table 1:** Performance of the Controller for 3 Phase Fault on Line 3-4 for 10msec

The test system is simulated with PSS for a three phase fault on line 1-2.The SVC is connected at midpoint and the fault is cleared in five cycles. The speed, rotorangle oscillations in G2 & voltage at G2 are very small. Therefore, it is appropriate to discuss G1 only. With PSS only, the difference in rotor angle oscillations are 0.8547 rad, rotor speed of G1 oscillates to 0.004 PU and voltage dip is 0.2 PU. The voltage reduces to very small value of 0.2 PU that leads to voltage collapse in power systems. To enhance the voltage profile, SVC is incorporated into the test system. But the system still experiences oscillations, but less in magnitude. The voltage at G1 is enhanced to 0.6 PU. The oscillation is due to the uncoordinated control of two controllers.. The PSS is first trained by ANFIS technique and the simulation results are shown in table I.

To coordinate controllers Adaptive NeuroFuzzy Inference System trained controller is used in PSS/SVC. The ANFIS trained controllers of PSS/SVC maintain the stability of the system in three phase faults, reduces the oscillations at G1 and settles to nominal rotor angle, and also improves the voltage profile after the clearance of the fault. The adaptive, intelligent, well trained controller manages the situation very well in critical disturbances

## VI. CONCLUSION

The greater dimensions make the dynamic programming technique impractical for nonlinear stochastic dynamic systems. For nonlinear systems, fuzzy logic controllers are well-established. It is possible to create a fuzzy logic controller that is optimal by using adaptive approaches. This study develops a fuzzy coordinated controller using neural networks for PSS and SVC-based stabilizers. The suggested controller enhances power system stability and is suited for damping oscillations. The proposed NeuroFuzzy external controller is effective in improving the overall power system damping, according to simulation data that have been provided.Without the need for a power system mathematical model, the NeuroFuzzy controller can deliver nonlinear near-optimal control.

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