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Design and Comparative Analysis of an Adaptive-Network-Based Fuzzy PSS, Robust Fuzzy PSS and Conventional PSS for Damping Low Frequency Electro -Mechanical Oscillations

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Abstract: *This paper deals with the design of an Adaptive-Network-Based Fuzzy Power System Stabilizer (ANFIS PSS) to improve the small signal stability. The proposed Power System Stabilizer (PSS) provides a natural framework of multi-layered feed forward adaptive network, which uses the fuzzy logic inference system. In this proposed approach, the hybrid-learning algorithm can tune the fuzzy rules and the membership functions of the PSS. The dynamic performance of the system with ANFIS PSS has been investigated under different operating conditions and system parameters. For comparative studies, the conventional design of PSS (CPSS) and Fuzzy logic based PSS(FPSS) are also implemented and compared with proposed PSS for the above operating conditions & change in system parameters. The experimental results demonstrate that the proposed PSS performs well in both damping and also in quicker response than the other two designs.*

Keywords: *Power System Stabilizer, Small Signal Stability, ANFIS PSS, Hybrid learning algorithm.*

1. Introduction

Power Systems are in general nonlinear and often exhibit low frequency electro- mechanical oscillations due to insufficient damping. To overcome this problem, Power System Stabilizers (PSS) are used which provide the supplementary stabilizing signal to suppress the generator electro-mechanical oscillations and enhance the small signal stability of power system.

The fixed structure PSS, designed using a linear model obtained by linearizing the nonlinear model [1] around a nominal operating point provides optimum performance for the nominal operating condition and change in system parameters. But this PSS is not robust. The performance becomes suboptimal following deviation in system parameters and loading condition from their nominal values.

In recent years, new artificial- intelligence based approaches have been proposed to design adaptive and robust PSS to provide optimum damping to the system oscillations over a wide range of system parameters and loading conditions. These approaches include Fuzzy Logic [2-5], Neural Networks [6-8] and genetic algorithm [9,10].Fuzzy Logic based PSS shows great potential in increasing the damping of generator oscillations, especially when made adaptive(i.e.) tuned by neural network [11,12]. Ruhua You [13] discussed about the performance of ANFIS PSS (which uses the change in speed and active power deviation as input signals) with the plant identifier. In that paper due to plant identification model and recursive least Square algorithm, complexity was increased. In the paper [14], real –time tests were performed on a physical model of a power system employing a PHSC2 Programmable Logic Controller as an AVR and Digital Signal Processor as a stabilizer. This PSS uses active power generation and its deviation as input signals. In the paper [15], Neuro Fuzzy modeling possesses the advantages of fuzzy modeling and neural networks in general manner. The basic concepts of ANFIS are explained in [16].

In this paper, an adaptive-network-based fuzzy logic power system stabilizer which uses speed deviation $\Delta\omega$ and acceleration $\Delta\dot{\omega}$ as input signals with the training of hybrid learning algorithm, which is based on error back propagation and least square error estimate technique is developed. The proposed approach brings the learning capabilities of Neural Network (NN) to the robustness of Fuzzy Logic System (FLS) in the sense that Fuzzy logic concepts are imbedded in the network structure and operation. The proposed adaptive network based fuzzy logic PSS has the property of learning (i.e.,) fuzzy rules and the membership functions of the controller can be tuned using a hybrid learning algorithm.

This rest of the paper is organized as follows: Section 2 discusses about the system investigated. Section 3 presents System with the CPSS Design and FPSS Design. Section 4 presents the proposed ANFIS PSS design & hybrid learning algorithm and the dynamic performance of the system with this design. Section 5 demonstrates the Simulation results. Section 6 presents the conclusion.

2. System Investigated

The system investigated comprises a synchronous generator connected to an infinite bus through a double circuit transmission line. IEEE type ST1A excitation system model is considered. The Single line diagram of the SMIB system and this system data is given in the Appendix 1.Figure 1 shows the schematic block diagram of the SMIB system with PSS.

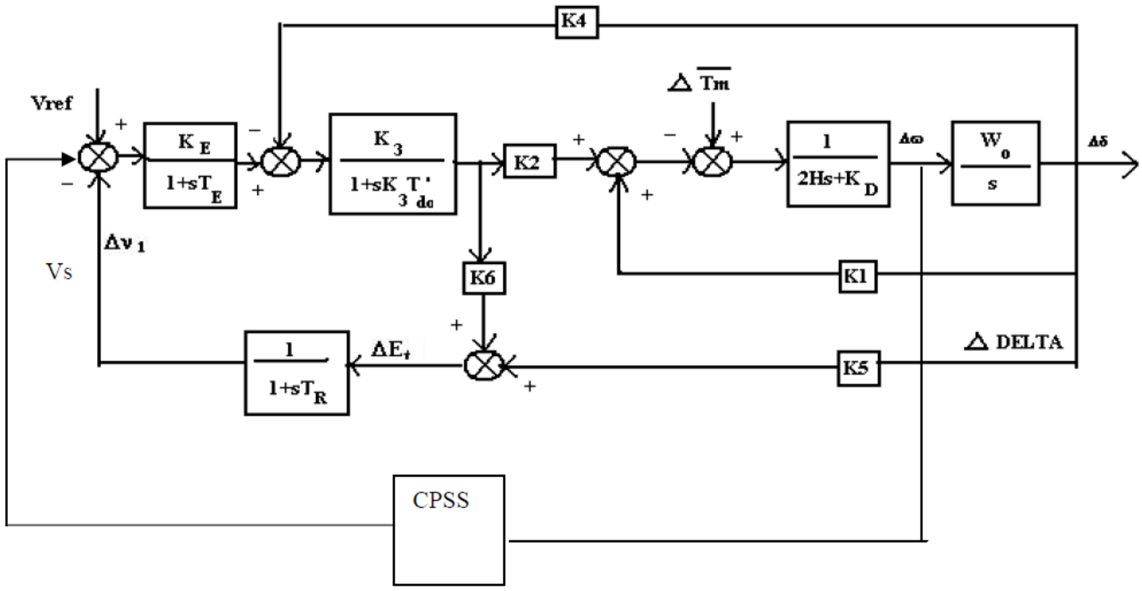

Figure1. *Structure of the SMIB system with PSS*

3. CPSS and FPSS Design

CPSS has a transfer function consisting of a wash–out block, a lead-lag phase compensator circuit and a stabilizer gain block.. The structure of the used PSS is illustrated in Fig.2.

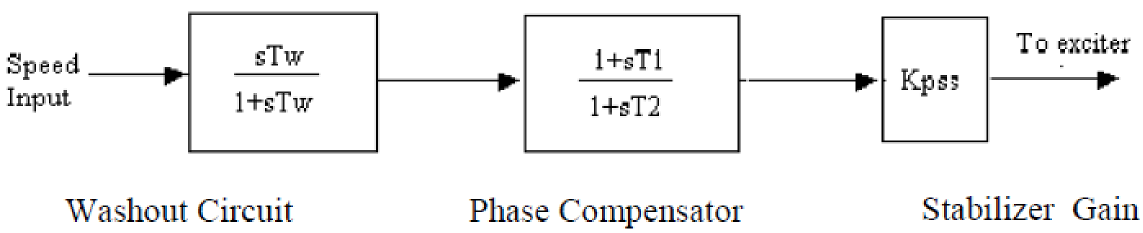

Figure2. *Conventional Power System Stabilizer (CPSS)*

The transfer function of the CPSS is given in equ (1):

$$\Delta V_s = K_{PSS}\left(\frac{sTw}{1+sTw}\right)\left(\frac{1+sT_1}{1+sT_2}\right)\Delta\omega \qquad (1)$$

where K_{PSS} is the PSS gain, Tw is the washout time constant and T_1 and T_2 are the compensator time constants. A conventional PSS comprising a pair of cascade connected lead-lag network is considered for the conventional design. K_1 to K_6 are the Heffron –Philips constants as per Fig.1. The phase compensator time constant $\mathbf{T_1}$ is determined by phase compensation technique [1] which gives the necessary phase lead to compensate for the lag introduced by the excitation loop such that the stabilizer path provides torque changes in phase with speed changes. The gain Kpss for effective damping of the oscillations is calculated using trial & error method as follows: Kpss is varied for various values and every value the damping factor is calculated. An acceptable damping factor of 0.4 is assumed for a specification and the corresponding value is chosen as the gain of the stabilizer. The above procedure for calculating T_1 and Kpss is to be repeated for every operating condition in order to determine the optimum PSS settings.

3.1. Design of Fuzzy Logic Power System Stabilizer

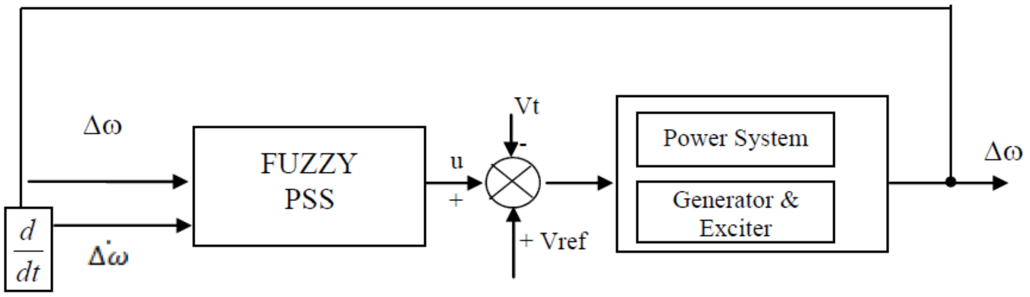

Figure3. *Structure of the SMIB system with FUZZY PSS*

Figure.3. shows the Structure of the SMIB System with FUZZY PSS. Speed Deviation of the synchronous machine (Δω) and its deviation ($\Delta\dot{\omega}$) are chosen as inputs to the FPSS. The inputs are normalized using their estimated peak values. Seven labels are taken for both the inputs and output. The labels are LP (large positive), MP (medium positive), SP (small positive), VS (very small), SN (small negative), MN (medium negative) and LN (Large negative). Linear triangular membership function is used in the design of FPSS. The fuzzy sets with triangular membership function for Δω are shown in Figure.4. The membership function for $\Delta\dot{\omega}$ and Vs are similar to the Figure.4.

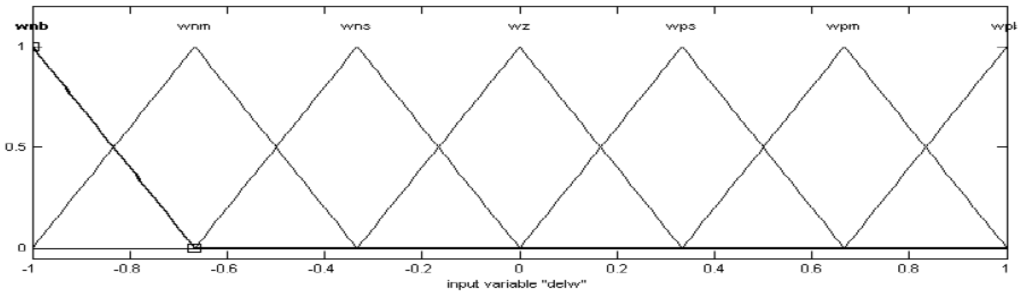

Figure4. *Triangular membership function of* $\Delta\omega$

Table-1 shows the rules of fuzzy logic based PSS. [6].

Table1. *Rule Table of fuzzy logic PSS*

		$\Delta\dot{\omega}$						
		LP	MP	SP	VS	SN	MN	LN
Δω	LP	LP	LP	LP	LP	MP	SP	VS
	MP	LP	LP	MP	MP	SP	VS	SN
	SP	LP	MP	SP	SP	VS	SN	MN
	VS	MP	MP	SP	VS	SN	MN	MN
	SN	MP	SP	VS	SN	SN	MN	LN
	MN	SP	VS	SN	MN	MN	LN	LN
	LN	VS	SN	MN	LN	LN	LN	LN

For defuzification, centroid method has been chosen.

4. Proposed ANFIS Design

The ANFIS structure consists of 5 layers. The explanation about each layer is given in this section. In Figure.5, that a circle indicates a fixed node whereas a square indicates an adaptive node (the parameters are changed during training). The adjustment of modifiable parameters is a two-step process. Fuzzy inference system (FIS) involves fuzzy rules for determining output decisions. In this paper, the rules are trained using the hybrid learning algorithm.

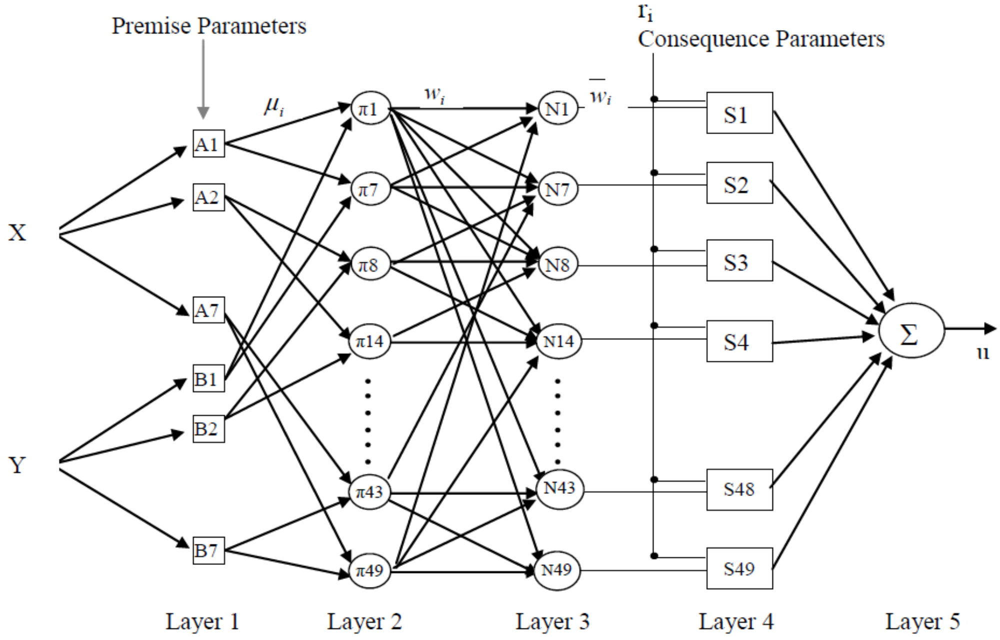

Figure5. *Diagram representing ANFIS structure*

4.1. Explanation of Each Layer

Layer 1: Calculate Membership Value for Premise Parameter

Each node in this layer is a square node with the node function.

$$O_i^1 = \mu_{A_i}(x) \tag{2}$$

where x is the input signal of the node i , and A_i is the linguistic labels (small, large …) associated with these node function.. In other words $\mu_{Ai}(x)$ is the triangular membership function of A_i and it specifies the grade of membership function.

$$\mu_A = \begin{cases} 0, & \text{if } x_i \le a - \frac{b}{2} \\ 1 - \frac{2\left|x_i - a\right|}{b}, & \text{if } a - \frac{b}{2} < x_i < a + \frac{b}{2} \\ 0, & \text{if } x_i \ge a + \frac{b}{2} \end{cases} \tag{3}$$

Node output: Membership value of input.

This layer is the **FUZZIFICATION** layer. All the nodes in this layer are adaptive nodes; $\boldsymbol{\mu_{Ai}}$ ***(x)*** is the degree of the membership of the input represented by the node. Parameters in this layer are referred to as **premise parameters** and they can be trained using the hybrid learning algorithm.

Layer 2: Firing Strength of Rule

Use T-norm (min, product, fuzzy AND...)

$$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \tag{4}$$

Node output: Firing strength of rule.

This layer represents the firing strength of the rule. The nodes of this layer are called rule nodes. Every node in layer 2 is a fixed node (not adaptive) and calculates the firing strength of each rule via multiplication of the incoming signals. This layer is also known as **FUZZY RULE LAYER**. These are labeled as $\prod$ to indicate that they play the role of a simple multiplier.

Layer 3: Normalize Firing Strength

Ratio of i^{th} rule's firing strength to all rules' firing strength

$$O_i^3 = \overline{w_i} = \frac{w_i}{\sum_{j=1}^{N} w_j} \tag{5}$$

where N is the no. of rules.

Node output: Normalized firing strengths

Normalization of firing strengths the i^{th} node calculates 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. These are labeled N to indicate that these perform a normalization of the firing strength from previous layer.

Layer 4: Consequent Parameters

Takagi- Sugeno type output:

$$O_i^4 = \overline{w_i} r_i = \frac{w_i}{\sum_{j=1}^{N} w_j} r_i \tag{6}$$

where { r_i}consequent parameters

Node output: Evaluation of Right Hand Side Polynomials.

All the nodes in this layer are adaptive nodes. The output of each node is simply the product of the normalized firing strength and individual rule output of corresponding rule which also known as **consequence parameters**. Output of this node is equal to the weighted consequent part of rule table.

The rule matrix of the Takagi-Sugeno model is given in Table 2 [14]. This table contains the consequence parameters (r).

Table2. *Rule Matrix of the Takagi-Sugeno Fuzzy model*

		Δω						
		LP	**MP**	**SP**	**ZE**	**SN**	**MN**	**LN**
Δω	**LP**	1.0	1.0	1.0	1.0	0.66	0.33	0.0
	MP	1.0	1.0	0.66	0.66	0.33	0.0	-0.33
	SP	1.0	0.66	0.33	0.33	0.0	-0.33	-0.66
	ZE	0.66	0.66	0.33	0.0	-0.33	-0.66	-0.66
	SN	0.66	0.33	0.0	-0.33	-0.33	-0.66	-1.0
	MN	0.33	0.0	-0.33	-0.66	-0.66	-1.0	-1.0
	LN	0	-0.33	-0.66	-1.0	-1.0	-1.0	-1.0

This layer is also known as the **DEFUZZIFICATION** LAYER. Each neuron in this layer represents a single output of the neuro-fuzzy system. It takes the output fuzzy sets clipped by the respective integrated firing strengths and combines them into a single fuzzy set. ANFIS can apply Sugeno defuzzification technique.

Layer 5: Overall Output.

$$O_i^5 = u = \sum_{i=1}^{N} \overline{w_i} r_i = \frac{\sum_{i=1}^{N} r_i . w_i}{\sum_{j=1}^{N} w_j} \tag{7}$$

Node output: Weighted Evaluation of RHS Polynomials

Sum of all incoming signals. This layer has only one node labeled 'S' to indicate that is performs the function of a simple summer. This neuron thus calculates the sum of outputs of all defuzzification neurons and produces the overall ANFIS output.

4.2. Hybrid Learning Algorithm [17]

The proposed adaptive network is trained by hybrid learning algorithm which is based on error back propagation and least squares estimate techniques. The ANFIS based PSS has the property of learning i.e. fuzzy rules and Membership functions of the controller can be tuned using a learning algorithm. The output of the adaptive network can be evaluated as

$$u = \sum_{i=1}^{N} \overline{w_i} r_i = \frac{\sum_{i=1}^{N} r_i . w_i}{\sum_{j=1}^{N} w_j} \tag{8}$$

where, $w_i = \mu_{A_i}(x) \times \mu_{B_i}(y)$ and

$$\mu_i = \begin{cases} 0, & \text{if } x_i \leq a - \frac{b}{2} \\ 1 - \frac{2\left|x_i - a\right|}{b}, & \text{if } a - \frac{b}{2} < x_i < a + \frac{b}{2} \\ 0, & \text{if } x_i \geq a + \frac{b}{2} \end{cases}$$

To apply the supervised learning on the network, it is necessary to define an error function. Modification of consequence parameters r_i, and premise parameters a_i and b_i require the evaluation of the error function partial derivatives for each parameter type. Expressions for the modifications of these parameters are as follows:

$$\varepsilon = \frac{1}{2}(u - d)^{2,} \tag{9}$$

$$r_i(t+1) = r_i - \eta_r \frac{\partial \varepsilon}{\partial r_i}, \quad i=1,\ldots\ldots, N; \tag{10}$$

$$a_i(t+1) = a_i(t) - \eta_a \frac{\partial \varepsilon}{\partial a_i}, \quad i=1,\ldots\ldots N \tag{11}$$

$$b_i(t+1) = b_i(t) - \eta_b \frac{\partial \varepsilon}{\partial b_i}, \quad i=1,\ldots\ldots N \tag{12}$$

where u is the actual output ,d is an expected output of the controller, coefficients η_a , η_b, η_w determines the speed of a corresponding parameter training , N is the no. of fuzzy rules. Expressions for calculation of the error function partial derivatives, used for weights modification, can be evaluated as:

$$\frac{\partial \varepsilon}{\partial r_i} = \frac{\partial \varepsilon}{\partial u} . \frac{\partial u}{\partial r} = \frac{(u-t).w_i}{\sum_{i=1}^{N} w_i} \tag{13}$$

$$\frac{\partial \varepsilon}{\partial a_i} = \frac{(u-t)(r_i\_u)w_i \operatorname{sgn}(x - a_{i)}}{\mu A_i b_i \sum_{j=1}^{N} w_i} \tag{14}$$

$$\frac{\partial \varepsilon}{\partial a_i} = \frac{(u-t)(r_i\_u)w_i \left|(x - a_{i)}\right|}{\mu A_i b_i \sum_{j=1}^{N} w_i} \tag{15}$$

4.3. Dynamic Response of the System with the Proposed ANFIS PSS

Using the training method, the parameters of the ANFIS PSS are updated based on the performance of the generator. Simulation studies were performed on a SMIB system. Three states were model the generator X= [$\Delta\omega$, $\Delta\delta$, $\Delta\psi_{fd}$]. The simulation was done in the Matlab Fuzzy logic toolbox. The ANFIS system is same as the fuzzy interface system except for the fact that here the fuzzy interface system is an adaptive neuro-fuzzy trained one. With the proposed ANFIS PSS applied to the study SMIB system, the Figure.6 shows the dynamic response of the generator rotor angle deviation as a function of time for P=0.8 p.u, Q = 0.6 p.u. It is clear that the proposed PSS is more effective than the one is proposed in [13] with the plant identifier model.

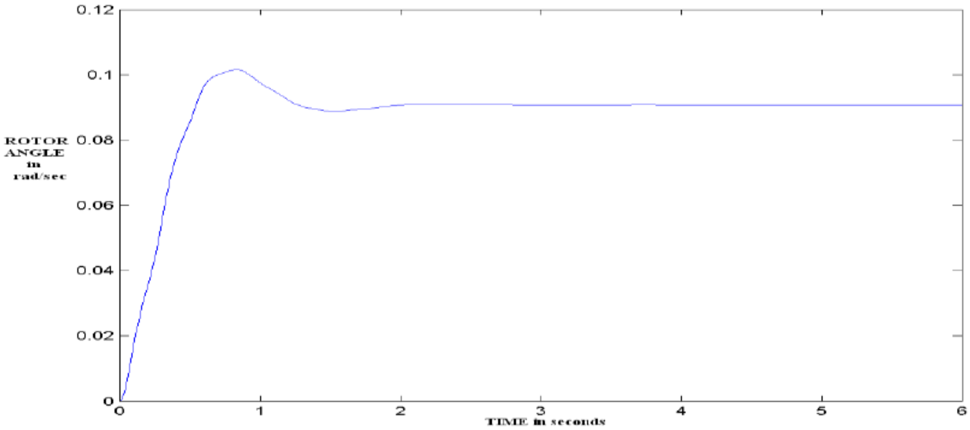

Figure6. *Dynamic response for operating condition P = 0.8p.u, Q = 0.6p.u. & X_e = 0.4752p.u.*

5. Simulation Results

For various operating conditions and system parameters, the dynamic response of the generator rotor angle deviation of the SMIB system for conventional, fuzzy and adaptive neuro fuzzy was simulated using MATLAB simulink/Fuzzy Logic toolbox / ANFIS toolbox. Figure 7.1 to Figure 7.7 shows the comparative graphs of the dynamic responses of CPSS, FPSS and ANFIS PSS.

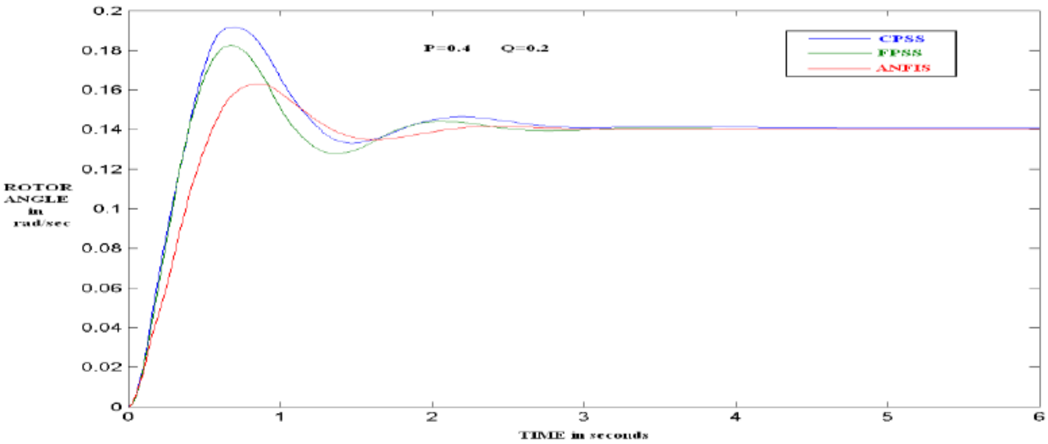

Figure7.1. *Response for operating condition P = 0.4p.u, Q = 0.2p.u, X_e = 0.4752p.u. (Lightly loaded condition)*

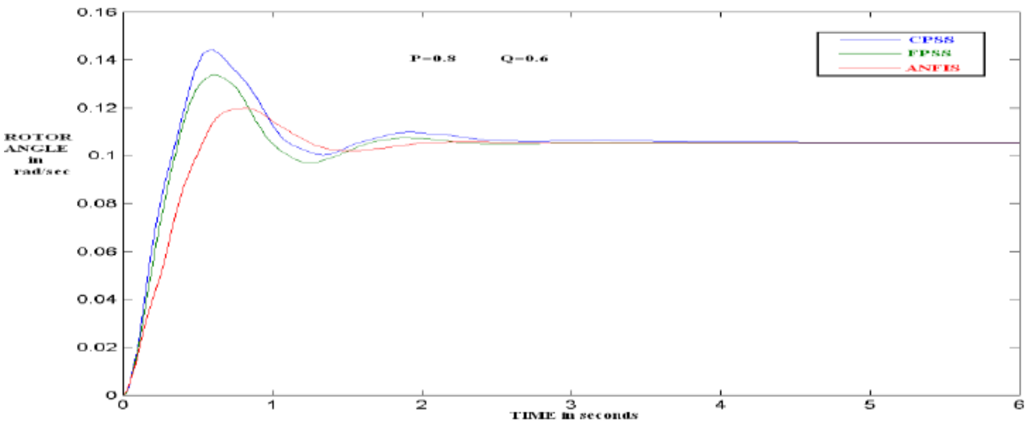

Figure7.2. *Response for operating condition P = 0.8p.u, Q = 0.6p.u, X_e = 0.4752p.u. (Lightly loaded condition)*

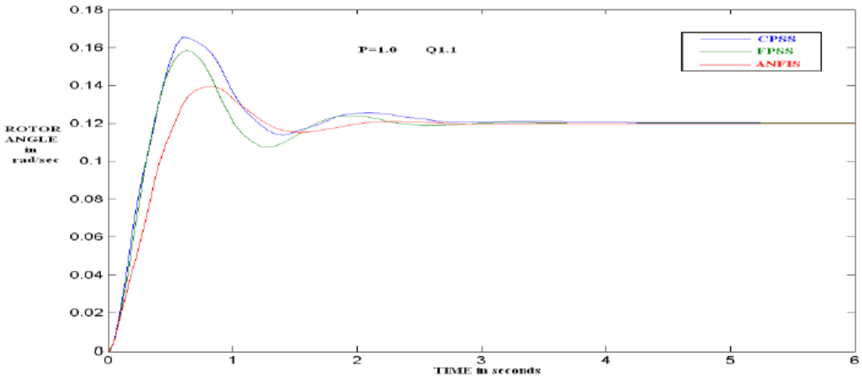

Figure.7.3. *Response for operating condition P = 1.0p.u, Q = 1.1p.u,* X_e *= 0.4752p.u. (Nominal loading condition)*

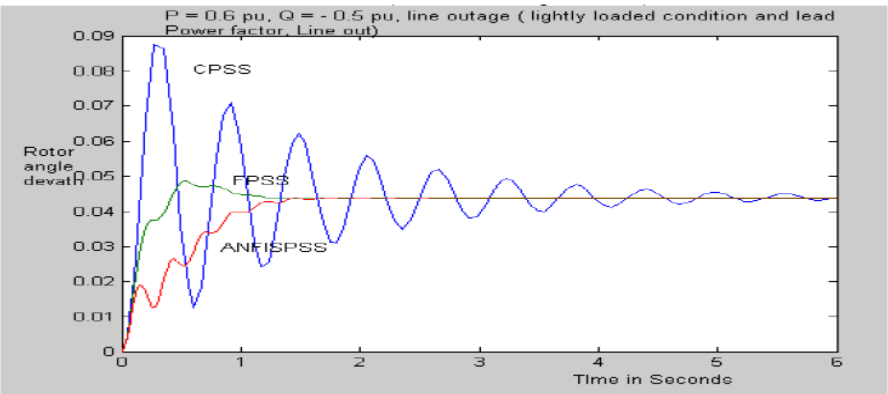

Figure.7.4. *Response for P= 0.6p.u, Q = -0.5p.u, line outage (Lightly loaded condition, leading power factor, line outage)*

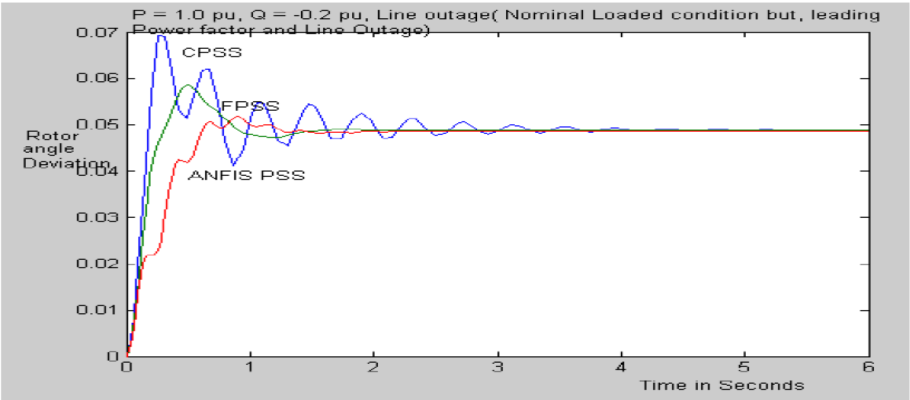

Figure.7.5. *Response for P= 1.0 p.u, Q = -0.2p.u, line outage (Nominal loaded condition, leading power factor, line outage)*

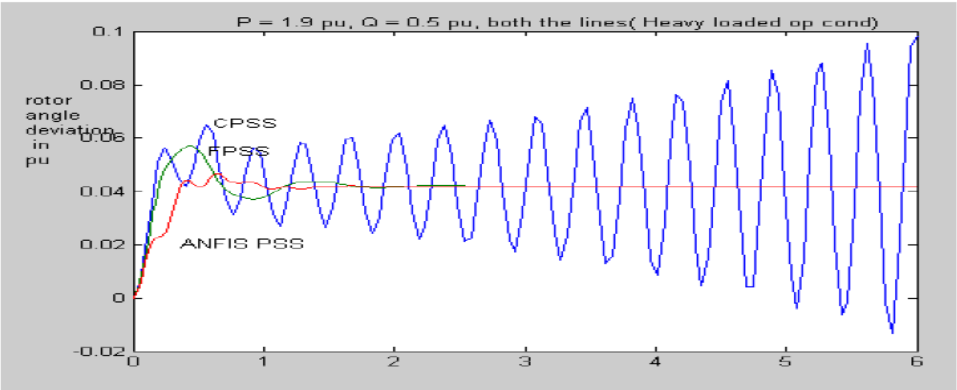

Figure.7.6. *Response for P= 1.9p.u, Q = 0.5p.u (Heavily loaded condition)*

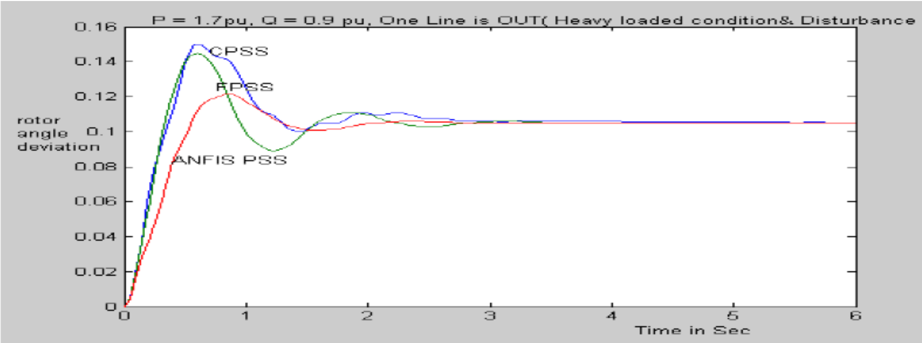

Figure.7.7. *Response for P= 1.7 p.u, Q = 0.9p.u, line outage (Heavily loaded condition and change in system parameter)*

After analyzing the responses of the system for conventional, fuzzy and adaptive neuro controllers, the following points were inferred.

1. Adaptive neuro fuzzy controller had better control action over the conventional controller and fuzzy controller.
2. The response of Adaptive neuro controller had less overshoots over conventional and fuzzy controllers.
3. Minimum settling time. The Comparison of the settling time of these PSSs were shown in Table 6 in the Appendix.-2

6. Conclusion

The real time response of the non-linear system considered here reveals that the ANFIS based controller provides better response over the conventional controller. The settling time was minimum and the response showed minimum overshoots. On concluding this paper, we infer that ANFIS controller can be implemented for SMALL SIGNAL stability in power systems for quicker control action. ANFIS based tuning of PSS is developed for a single machine connected to infinite bus (SMIB) system. The simulations results through MATLAB simulink shows exceptionally good damping of low frequency electromechanical oscillations for wide range of operating conditions.

The ANFIS design has an edge over both conventional and Fuzzy designs. The time taken to stabilize the power system is less compared to both the alternate designs. When a system undergoes oscillations, large time taken for tuning PSS could prove disastrous. Prolonged oscillations may lead to isolation of generating units or worse, shutdown of generating station. Hence the ANFIS designed PSS proposed could if used prove to be much safer and could enable the power system engineers to maintain a higher degree of system security

The ANFIS developed in this research work has been designed for an SMIB system. But practical systems are multi-machine systems where load variations, which are continuous, would affect the load distribution among the various units connected to the system. The inter-area modes will lead more oscillatory instability.

For such systems, the machine or group of machines that contribute to the oscillations will have to be identified and the PSS on the identified machines will have to be tuned. The ANFIS approach can be extended to such practical systems by including the problem of identification of the machines.

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APPENDIX -1

Data for Single Machine Infinite Bus System

Table3. *Line Data – SMIB System*

Base MVA: 100 Frequency: 50 Hz.

From Bus	To Bus	No.of Circuits	R (p.u.)	X (p.u.)	B/2 (p.u.)
1	2	2	0.0	0.4	0.0

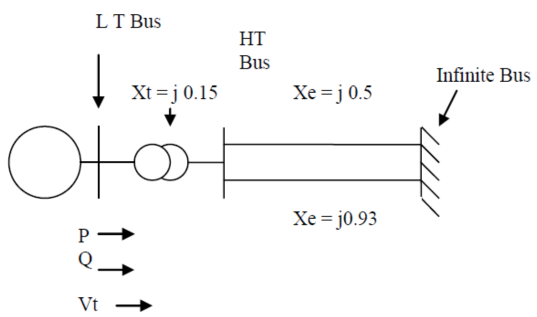
Table4. *Synchronous Machine Data – SMIB System*

Parameters are in p.u. with respect to machine rating

r_a (p.u.)	x_d (p.u.)	x_q (p.u.)	x_d' (p.u.)	x_q' (p.u.)	T_{do}'(s)	T_{qo}'(s)	H(s)	D
0.0	1.6	1.55	0.32	0.0	6.0	0.0	5.0	0

Table5. *Excitation System Data – SMIB System*

K_E	T_E (s)	T_R (s)
200	0.05	0.02



Xd` = j 0.3

H = 3.5MW s / MVA

Synchronous Generator

X = 0.4, X_d = 1.6, Xq =1.55, X_d` = 0.32 1.55, $X_q$` = 0

T_{do}` = 6.0, T $_{qo}$`= 0, H= 5.0

K_E= 200, T_E = 0.05, T_R = 0.02

APPENDIX-2

Table6. *Comparison of Settling time of the dynamic responses of rotor angle deviations of the study system with CPSS, FPSS and ANFISPSS*

S.No.	P	Q	SETTLING TIME		
			Conventional PSS	FPSS	ANFIS
1	0.6	0.3	2.319586	2.233492	1.725625
2	0.7	0.3	2.275656	1.93971	1.273631
3	0.7	0.4	2.270549	1.933231	1.704156
5	0.8	0.3	2.127308	1.674679	1.249432
6	0.8	0.4	2.225263	1.309407	1.230209
7	0.8	0.5	2.273081	1.942073	1.649288
8	0.9	0.3	2.073232	1.406958	1.238119
9	0.9	0.4	2.12317	1.493872	1.221584
11	1	0.3	2.023692	1.33128	1.200007
12	1	0.4	2.06369	1.442593	1.177906
13	1	0.5	2.061296	1.636016	1.179635
14	1	0.6	2.169134	1.890441	1.575382
15	1	0.7	2.219698	1.852795	1.624489
16	1.1	0.3	2.080105	1.537151	1.168116
17	1.1	0.4	2.068153	1.649789	1.158295
18	1.1	0.5	2.068681	1.600719	1.169381
19	1.1	0.6	2.050719	1.919589	1.558155
20	1.1	0.8	2.214138	1.982808	1.642976
21	1.2	0.4	2.076965	1.583072	1.137989
22	1.2	0.5	2.016769	1.644264	1.157952
23	1.2	0.6	2.066309	1.718209	1.520238
24	1.2	0.9	2.27534	2	1.628217
25	1.3	0.5	2.071032	1.642968	1.118346

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Mahabuba received her B.E., M.S, M.E and Ph.D degrees in Electrical Engineering with terminal degree specialization in Electrical Power Systems from Madras University, Bits Pilani M.I.T and Anna University, Chennai, India respectively in 1994, 1998, 2003 and 2009 respectively. She is currently working as an Assistant Professor in Department of Electrical Engineering, College of Engineering, Al Ghurair University, Dubai, United Arab Emirates. She has been working with Al Ghurair University since 2007. Before this experience she has been worked in B.S.Abdur Rahman University, Chennai, India for 13 years. Her research interests are the following:

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- Low frequency oscillations, Mitigation of Oscillations.
- Artificial Intelligence techniques applied to Power Systems.
- Linear and Nonlinear control theory applied to Power Systems.