An Adaptive Neuro-Fuzzy based on Reference Model Power System Stabilizer

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Abstract - **This paper proposes novel technique for multi – machine power system stabilizer using an adaptive Neuro- Fuzzy inference system based on Error reference model (ERANFIS). The adaptive Neuro- Fuzzy inference system based on Error reference power system stabilizer (RNFIS PSS) It utilizes a first-order Sugeno fuzzy logic controller (FLC), the enrollment and outcome function of that is additionally configured online using a neural network accordance with the gradient descent training algorithm based on the reference error model.**

The simulated power system consists of single – machine – infinite – bus and multi – machine power system. The proposed ERANFIS PSS are designed for each machine. The simulation results use Matlab and S-function technique for various test, and it shows that the proposed stabilizer (ERANFIS PSS) has better performance than that of conventional power system stability (CPSS).

Keywords: **Multi–machine power system stabilizer, Neuro-Fuzzy inference system simulation.**

I. INTRODUCTION

The power systems' stabilization has been an important subject for reliability, because systems has become a large scale and complexity. Applications of modern control theory to damp oscillation at transient conditions in electric power system have been reported [1].

The PSS is commonly used on the synchronous generator. The well-known PSS is denoted by the traditional PSS (CPSS) and it is fastened parameter analog equipment. CPSS is introduced firstly in 1950 and it is based on the transfer function that is designed by using the classical control theory [2]. The phase difference from the input excitation control to the torque damping output has phase compensation network. By employing proper tuning approach for the phase and gain characteristics, the desired ration could be set.

Many techniques have been proposed to control synchronous generators in order to overcome stability problems. One of the most basic techniques is to introduce damper winding in synchronous generator [3,4] to damp out the speed oscillations , other methods include governor control [5], and excitation control [6,7,8] .. Designed using classical control theory, conventional PSSs (CPSSs) have been able to improve the stability limits of the system. However, their performance may deteriorate with change of the operation point. this is often as a result of the traditional PSSs ar designed employing a linearized model of the instrument at a endorsed operating point. in practice the power systems are extremely non-linear with stochastic operation in nature , controller parameters that are optimum for one set of operating conditions , may not be optimum for another set of operating conditions [12] . This made the way for additional research utilizing trendy control techniques [9, 10].

The adaptive neural fuzzy inference system power system stability (ANFIS PSS) is proposed by R. You [11]. He utilized a (Zero-order) of Sugeno FLC, which is membership functions and outcomes are additionally activated on-line throughout the utilization of an artificial neural network (ANN) system.

In this paper the technique of an adaptive neural fuzzy inference system by Jang [12], is used with error reference model to designed new method of Power System Stabilizer (PSS) for multi-machine power system called (ERANFIS PSS). A point by point depiction of the expected technique (ERANFIA PSS) will be found in the next sections. The simulation of the results for associate an unending tire arrangement of machines and systems with different trailers are introduced beneath to exhibit the viability of the suggested strategy.

II. POWER SYSTEM MULTI-MODE OSCILLATIONS

There are three procedure of oscillation in various – machine power system [12]:

(A) **Local Mode -** This is due to the oscillations that occur in the transition system and are derived from the vibrations of the generator rotors with relevancy to the joined proportional inertia of the system. it can be explained just as an oscillation of a generator comparative to an unlimited bus formed by the external combined equivalent inertia for a practical generator, as shown in the SMIB. The magnitude of the frequency has direct relevance to the equivalent movement inertia and also the prime mover to the (synchronous torque coefficient) connecting of the generator to the constant (bus-local) procedure vibration within the range from (0.5 to 1.5) Hz.

(B) **Inter – Machine Mode** – This mode is described the frequency of the carefully coupled generators which are swaying comparative to every each other's. That is often occurring at the plants with drives constituted from generators and controllers or nearby factories that are connected together with inter-ties. Where, the machines are connected or coupled to the equivalent machines inertia and coupled generator groups. The range of that frequency is 0.8 to 2 Hz.

(C) **Inter-area Mode -** These frequencies stern from coherent group of generators one area swaying for proportionate with various of other gatherings in other are Inter-territory frequencies area in range from (1.0 - 0.7)Hz and the particular these frequencies could interfere together with frequencies detailed underneath the another two techniques.

III. PROPOSED (ERANFIS PSS) DESIGN

The structure of power system stabilizer as have seen in figure 1 and it comprises of three subsystems, that area unit the symbol identifier for the generator, the (ANFIS PSS) and error reference model (ERM). In light on the error between the determined deviation of the generator speed (Δω) and it is the real value (Δω), the identifier parameters are updated. While, the adaptive neuro-fuzzy inference system (ANFIS),Power System Stabilizer (PSS) parameters are attuned by back-propagating the error signal between (Δω) and output values (Δωed) from error reference model (ERM) as have seen in figure 1. The system identification is therefore necessary for the prosperous setting of the block of (ANFIS PSS).

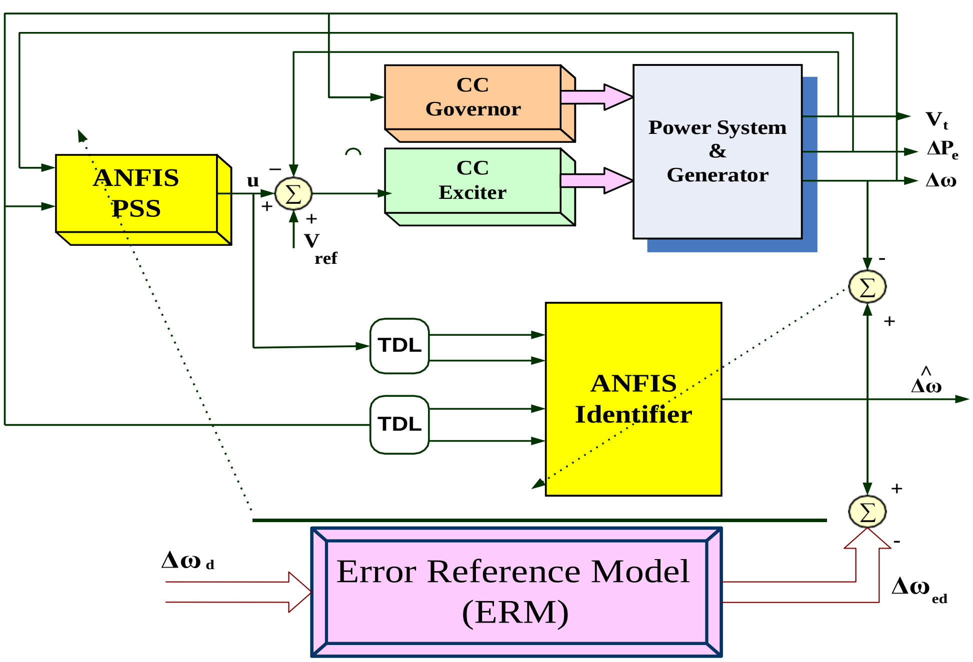


Fig. 1 Structure of the Proposed (ERANFIS PSS)

(1) The Error Reference Adaptive Control (ERMAC) :

This technique is proposed by Ali?. [13] for the neural network forward controller. One of the most important operation factors of neural network in in training and control is the tracking error or deviation between a desired value and the corresponding output value. In most cases network adaptation depends the magnitude and design of that error. Most weight update algorithms stand directly or indirectly on the tracking error of the plant unsteady of the system output and input.

This proved to show many advantages over standard control algorithms such as the (MRAC) which deal directly with system output and desired output. The advantages of new algorithm can be shown throw analyzing the major blocks of the algorithm. Fig (2) shows the general architecture of the Error reference model adaptive controller.

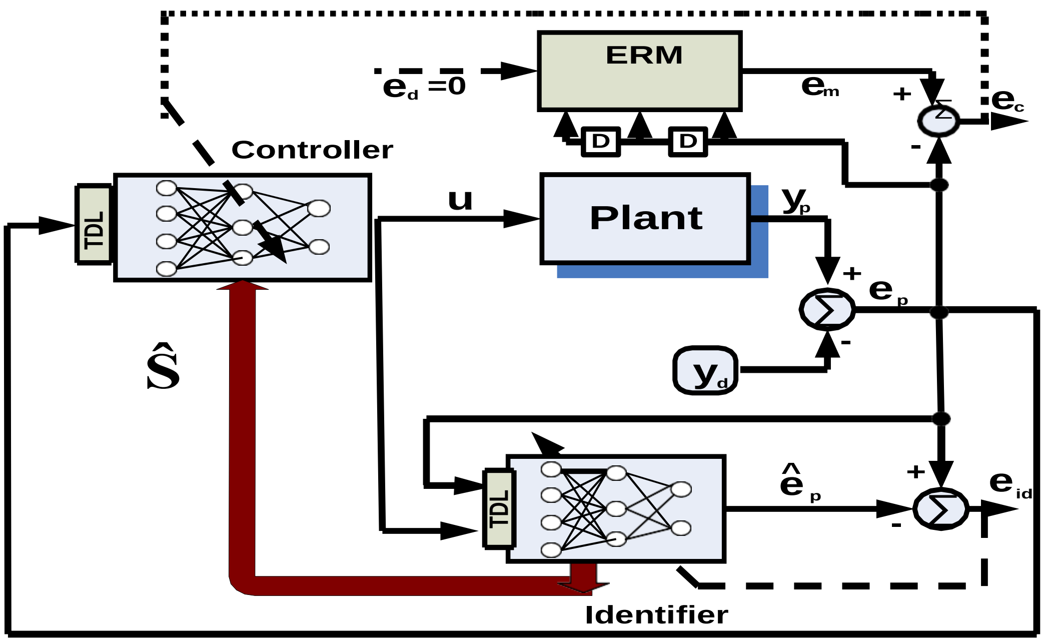


Fig 2 Error Reference Model Adaptive Controller (ERMAC)

The error reference model block, which is the upper part of the schematic shown in Fig (2) is the error reference model unit. It is the most important unit in this type of controller. First it is necessary to understand the function of a general reference model technique implement in control algorithms. For complex systems of un modeled dynamics, it found that, it is efficient to present a model of an order equivalent to that of the system to be controlled. Figure (3) shows the block diagram of reference model and the step response. It is clear from fig (3) that desired output (y_d) raises from zero to 1 a time equal zero. This is the case in all step inputs. Nothing worse for Neural Network (NN) than trying to track such signal directly. This is because it is not possible for any real plant to raise from (0 to 1) at zero time and correspondingly a tracking error is already existing. Since all NN training algorithms stand on the tracking errors, the NN thinks that it must tune their weights to accomplish this error which may cause improper tuning. If the desired value (y_d) is smoothed by proper model of be controlled the output may be smooth similar to (y_m) shown in fig.(3) properly by selecting reference model dynamics yield to proper tr from (0 to 1). This time is called the rise time and it is one of the characteristics of the reference model [13]. Now, if the signal (ym) is fed to the NN instead of (y_d) it is possible to be tracked with reasonable tracking error. This is the main idea standing behind the use of reference model in NN controllers.

Reference models are necessary especially for systems with delays. The transfer function of the reference model is shown in figure (3) and form that, the equation can be derived as:

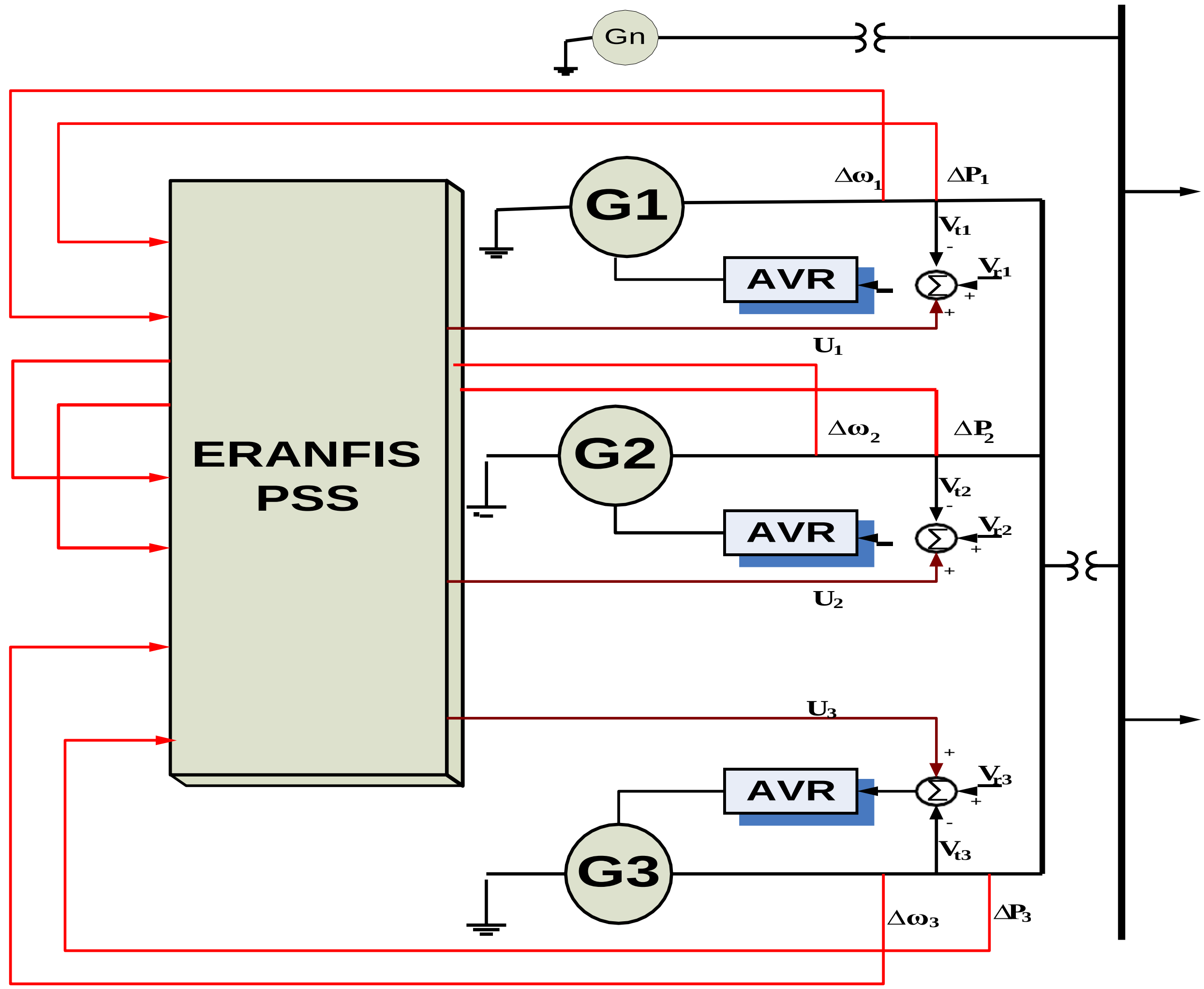


Fig. 3 Reference Model Response

$$M(s) = \frac{y_m(s)}{y_d(s)} = \frac{b_0}{s^r + \dots + a_1 s + a_0} \tag{1}$$

Where **r is** the relative degree of the model. The model reference considered here is of second order. For second order model (r=2), the transfer function of the reference model is:

$$M(s) = \frac{\omega_n^2}{s^2 + 2\varsigma\omega_n s + \omega_n^2} \tag{2}$$

Over shot:

$$Mp = \begin{cases} e^{-\xi\pi/\sqrt{1-\xi^2}} & 0 < \xi < 1 \\ 0 & 1 \leq \xi \end{cases} \tag{3}$$

Rise Time [94]:

$$t_r = \frac{\pi - \tan^{-1}\left(\frac{\sqrt{1-\xi^2}}{\xi}\right)}{\sqrt{1-\xi^2}\,\omega_n} \leq \frac{3.358}{\omega_n} \tag{4}$$

(2) ANFIS PSS Structure :

First order Sugeno-type fuzzy controller with linear rules has been used for ANFIS PSS, whose block diagram is given in figure 4. From the network representation of the fuzzy logic system, it is clear that back-propagation could be applied in order to adjust the parameters in membership functions and inference rules. The inputs of the PSS are speed and electrical power, which are passed through a washout filter so as to eliminate any existing dc offset. The first scaling block maps the real input to the membership functions are defined. The second scaling block is used to map the output of the fuzzy inference system to the real output needed. The fuzzy inference system consists of the fuzzification block, rules table block and Tankage and Surgeon's type defuzzification block [12].

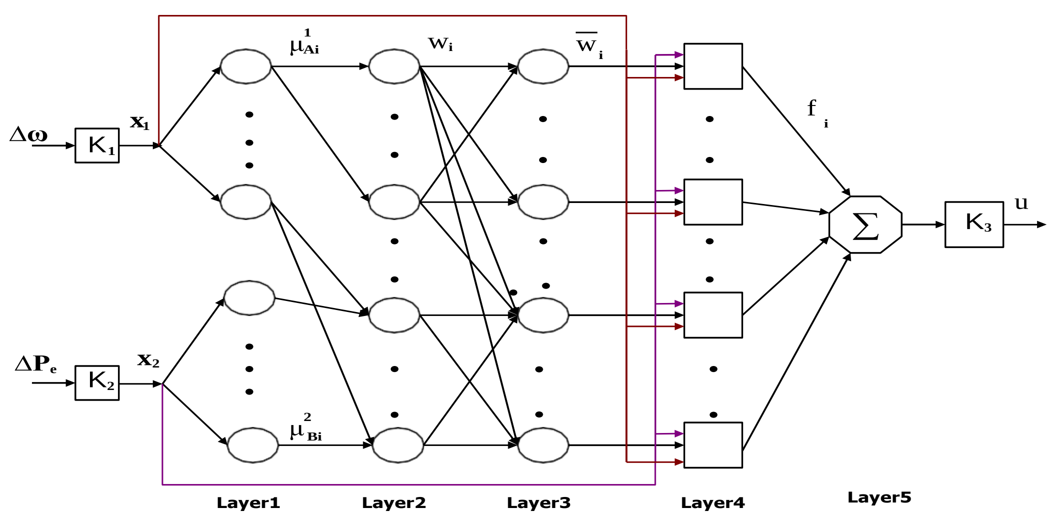


Fig. 4 Block diagram of the Neural Network of the (ANFIS PSS).

The rule design of fuzzy control is depends on a comprehension of the function and the control impact acquired from experiment. Rules are made utilizing generator acceleration power (Pacc = mechanical shaft power (Pm), generator electric power (Pe) and speed deviation ($\Delta\omega$) as control factors.

In real experiment, it is complicated to measure Pm and therefore the sum. Because of the slow restraint of the controller (related with the excitation reaction), it is presupposed that Pm may be a stationary starting with one sample then onto the next, subsequently: $\Delta P_m = P_m - P_{mo}$ is thought to be zero. Whilst $\Delta P_e = P_e - P_{eo}$ can alteration from model to model. Pmo and Peo are the stable-state value of Pm and Pe respectively, Pmo = Peo. Accordingly an outcome, (Pacc – Pm – Pe ≈ - ΔPe) is utilized in the improvement of the rule function. Every fuzzy if – thereafter rule of first order Takage and Surgeon's type [12]:

IF X_1 is A_i and X_2 is B_i THEREAFTER $U_i = P_i X_i + q_i X_2 + r_1$

Where X_1 , X_2 is input variables ($\Delta\omega$, ΔP_e) and A_i , B_i are linguistic variables , U_i is output of the ith rule and $\{p_i , q_i ,r_i\}$ is the consequent parameters set. The node function in each layer are of the same type function is described below:

Layer 1: Each node in this layer performs as Gaussiam member -ship (MF:

$$y_i^1 = \mu_{Ai}(X_i) = e^{-\frac{1}{2}\left(\frac{X_i - a_{ir}}{b_{ir}}\right)^2} \quad (5)$$

Where Xi is that the input for the point i, Ai is the lingual designation assignment to this point, and {ai, bi} is the Gaussian-shaped form of the MF parameters. y1i indicates the maximum degree to that this entry relate to the Ai linguistic characterization. With a crest value of 1 and a minimal value of 0. As the values of these parameters change, the Guassian-shaped functions forms of member ship functions. Actually, all functions that can be continuously differentiated piece by piece, for example, trapezoidal or triangular (MF) membership functions, are in the same way capable candidates for knot functions in such layer

Layer 2: Each node at this level represents the ability to strip the rule. Therefore, the nodes achieve a fuzzy AND process:

Layer 3: On this layer estimate the normalized rigor of every statute:

$$y_i^3 = \bar{w}_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \qquad (6)$$

Layer 4: The output of every node in this stratum could be a weighted successive aspect of the rule stream:

$$y^4 = f_i = \bar{w}_i(p_i x_i + q_i x_2 + r_i) \quad (7)$$

Wherever (wi) is the outcome of layer three, and { pi , qi ,ri} is the parameters set.

Layer 5: the one node during layer calculates the overall outcome as the summation of every coming in signals:

$$y^5 = \sum_{i=1}^{n} f_i \qquad (8)$$

Hus a FLC with learning capacity has been built. So as accomplish the required input-output mapping. These parameters are refreshed by the given preparing training information and a gradient based teaching method represented beneath.

Assuming that the coaching informational set has P inputs and the outcome layer it has only one single node, it read the errors pth input of the coaching information data:

$$E_p = \frac{1}{2}(y_p - y_p^L)^2 \qquad (9)$$

Wherever y_p is the pth ingredient of the sought-after vector, and y_p^L is the pth ingredient of the real outcome vector. An immediate pass is performed for every coaching information, and then a recurrence through is utilized and thereafter the outset from the outcome level, to calculate (∂E_p) / (∂y_p) for every indoor nodes. For the outcome node:

$$\frac{\partial E_p}{\partial y_i^L} = -(y_p - y_p^L) \qquad (10)$$

For the interior nodes in layer k:

$$\frac{\partial E_p}{\partial_{i,p}^{k}} = \sum_{m=1}^{k+1} \frac{\partial E_p}{\partial_{m,p}^{K+1}}$$

$$\frac{K+1}{k} \quad m.p \quad i,p$$

∂

(1 1)

y

Where yki, p is the outcome of node at the set of level k, k1 is the quantity of hubs at level (k + 1).

Suppose that α is a characterized given to adaptation network parameter:

$$\frac{\partial E_p}{\partial \alpha} = \sum_{y^* \in S} \frac{\partial E_p}{\partial y^*} \frac{\partial y^*}{\partial \alpha} \quad (12)$$

Where the S is the arrangement of hubs which is outcomes depends on α. The objective is to limit the total error E= ∑ E p General learning rule:

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \quad (13)$$

In which η is the learning rate and

$$\frac{\partial E}{\partial \alpha} = \sum_{P=1}^{P} \frac{\partial F_p}{\partial \alpha} \quad (14)$$

Furthermore, like traditional neural network coaching [14], an impulse term has additionally been added to get best concurrence:

$$\Delta\alpha(t) = -\eta \frac{\partial E}{\partial \alpha} + \beta \Delta\alpha(t-1) \quad (15)$$

The symbol β is represented the momentum factor and Δα (t-1) is the alteration of αwithin the last step. The adaptive network is considered as a comprehensive package of a (multi – layer) feed forward neural network system (NNS) with supervised studying ability. The ANFIS has nodes of directional connections, who's decided which nodes are associated. Every one of these nodes has a specific function and this function is varying from node to another. The overall input-output function would decide the choice of each node to be used based on the achieved adaptive network.

In the ANFIS, there are adaptive parameters and are specified by the training algorithm program and may be refreshed to realize the specified (input-output) mapping. In related way to the ANN together with oversee algorithm, the training rule of adaptive network

IV. ERANFIS PSS TECHNIQUE APPLIED TO (SIMB)

At this section, an Adaptive Network depend Fuzzy-Logic Control (FLC) structure is utilized to designing a new power system stabilizer (ERANFIS PSS) for single machine system. The ANFIS is taken into account to possess two inputs, the generator speed deviation ($\Delta\omega$) and it is derivative ($\Delta\omega$), and one control outcome, Upss .furthermore, the rule based contained the fuzzy if thereafter basics of Takagi and Surgeon's first order type, where the rule's output is a linear collection of variables of input plus a fixed expression:

$$\text{IF } \Delta\omega \text{ is } A_i \;\&\; \Delta\omega \text{ is } B_i \text{ subsequently } U_{pss} = p_i\,\Delta\omega + q\,\Delta\omega + r_i$$

The end result's is weighted average of the result of every rule. (ANFIS-PSS) architecture as have seen in Fig. (3), where the node capacities at each level are explained, as previously in the previous section.

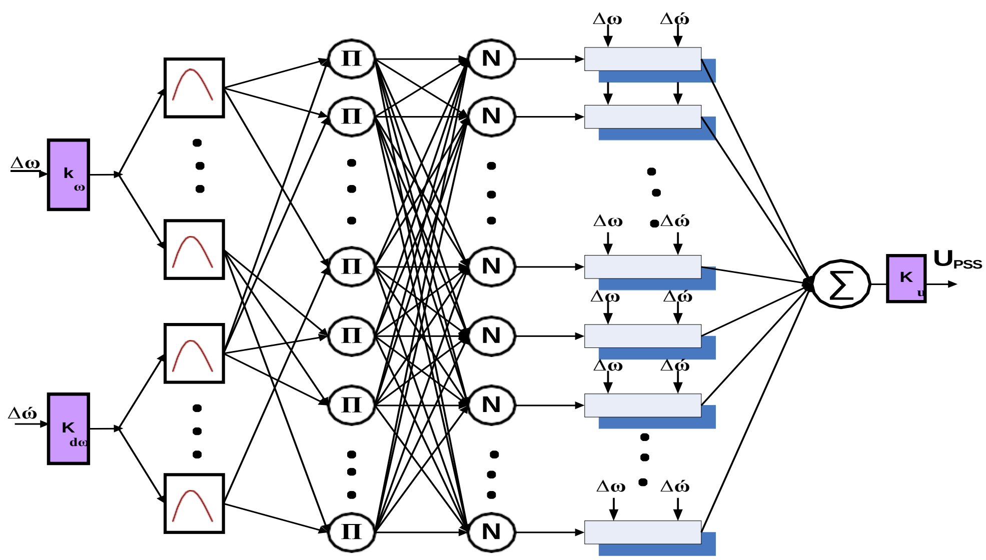


Fig. 5 Architecture of ANFIS 2-input -1-output PSS for SMIB

(1) ERANFIS PSS Training :

The parameters (MFs and rules) in the conventional fuzzy logic control (FLC) are determined by an expert who is knows about familiar with the system. Be that as it may, in the adaptive network-based fuzzy inference system (ANFIS) based on Power System Stabilizer (PSS), the initial worth of membership functions (MFs) parameters are evenly apportioned on the universes of discourse and every one resultant elements of basis table are set to 0. Depend on that, value of the ERANFIS PSS would begin from zero output and it reach gradually to the desired controller value throughout the training process. However practically, there is employing for the prior knowledge in the form of the unturned fuzzy if-then rules. Hence, the training would begin from much less error. The complexity of the training data and trial and error would determine the number of MFs for each input variable.

(2) System Configuration and Simulink Model

The impact of the approach stabilizer was thoughtful and the outcome was compared with those of conventional power system stabilizer (CPSS) and ERANFIS PSS. In conducted testing, CPSS was selected as associate analog kind offset-delayed controller, and ERANFIS power system stabilizer (PSS) is assumed to be a digital controller type with (Ts = 10 ms).

The generator is associated to the interminable bus by an electrical device (transformer) and dual parallel lines. Generator are provided with a speed controller and an (IEEE st3) kind irritation mode [15]. The system of diagram has been shown in Figure (6). In rapprochement, the conventional power system stabilizer (CPSS) was additionally involved in the study. A switch is utilized to reach at Variables among stabilizers.

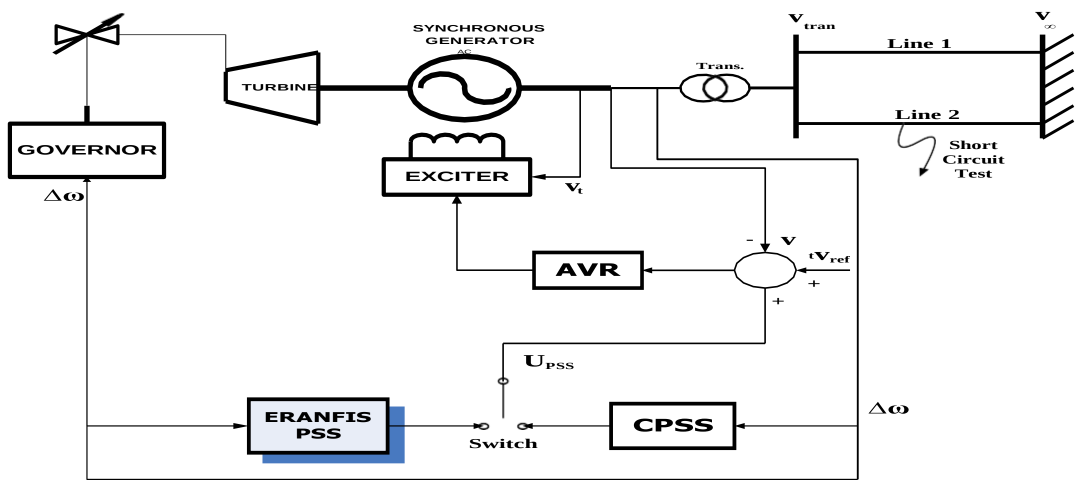


Fig. 6 SMIB System with PSS Model Configuration

The Matlab Simulink of SMIB with stabilizer circuit is shown in Figure (7). The parameters of the governor, Automatic Voltage Regulator (AVR), (CPSS), and further the (SMIB) parameters are Mentioned in (Appendix-A).

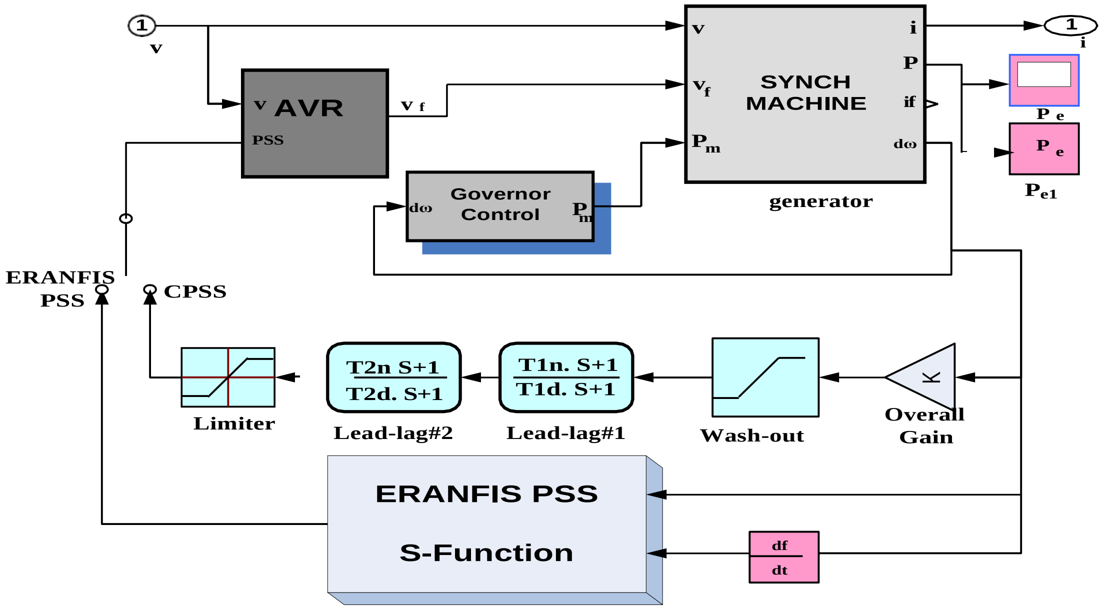


Fig. 7 Simulink Machine and PSS Control Block

V. SIMULATION AND RESULTS

To test the performance of the proposed stabilizer, a number of simulation studies have been performed to investigate the effectiveness of ERANFIS PSS at SMIB and compare it's with those of the CPSS.

The generator is operating at 0.8 p.u power and 0.9 pf lag , and 3-pahse short circuit occurred at 6 sec as shown in Fig.(6) and afterward cleared every 0.1 sec by opening the line. The transient response of the SMIB system as follow:

The figure (8) is shown the terminal voltage of the generator under 3-ph S.C Test. Generator Electrical output power deviation response under this test is shown in figure (10).

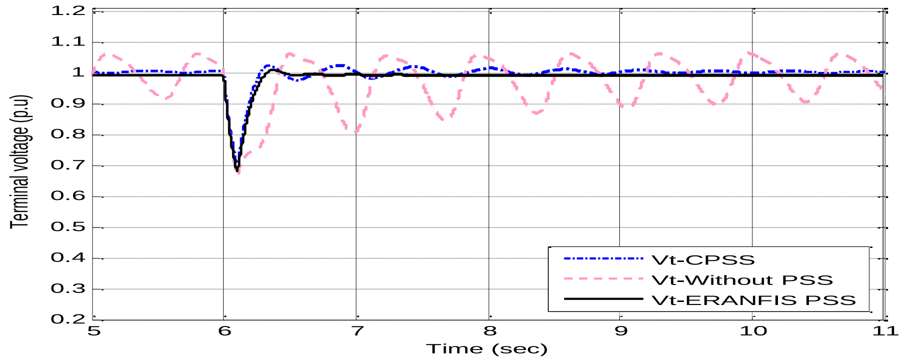


Fig .8 Generator Terminal Voltage Response under 3-ph S.C Test at 6 sec

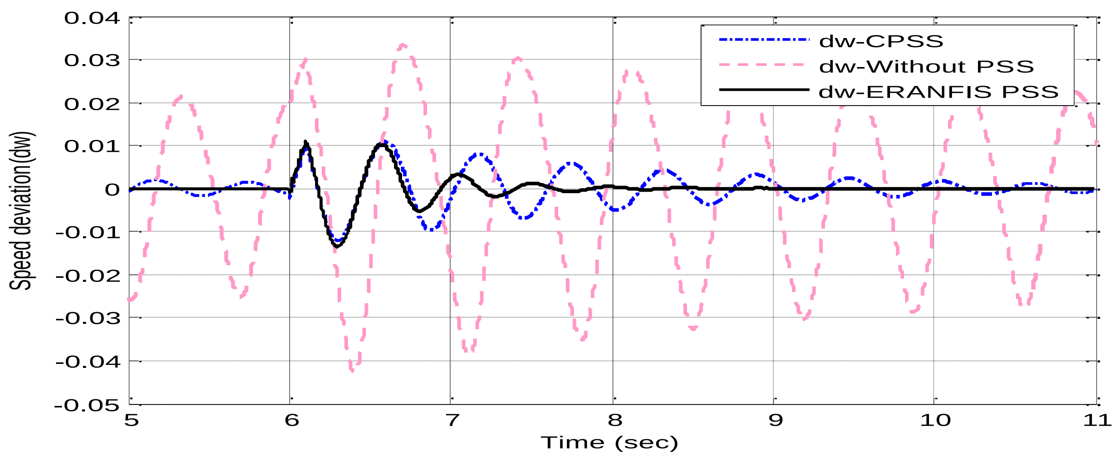


Fig. 9 Generator Speed deviation (dw) Response under 3-phase S.C Test at 6 sec

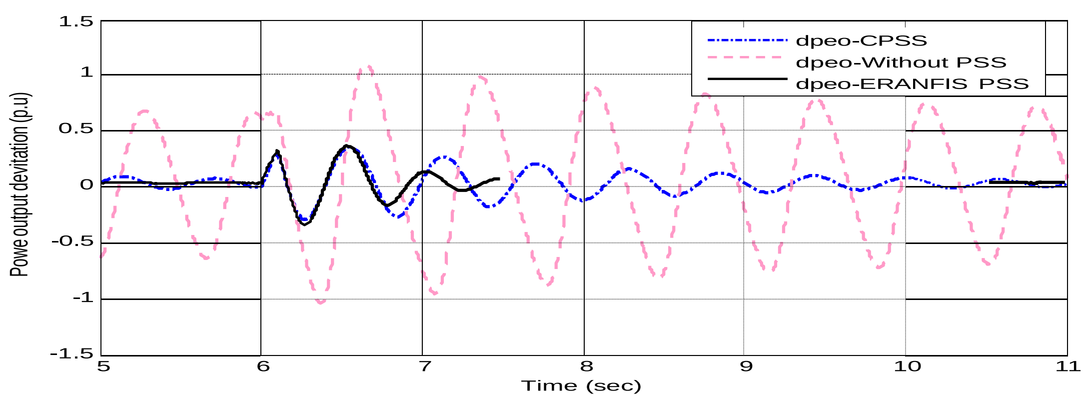


Fig. 10 Generator Electrical output power deviation Response under 3-phase S.C Test at 6sec

(A) Multi-machine System with ERANFIS PSS Technique

A model of an unlimited bus power system in a single machine is often utilized in stability studies into test the performance of a power system. However, it is rarely possible to model an actual power system by a SIMB model. A more realistic power system model can be obtained by considering the case of multi –machine power system. This section presents an extension of the proposed stabilization technique to multi-machine case, so that the efficacy of the proposed method in damping the multimodal oscillations in more realistic of the proposed method in damping the multimodal oscillations in more realistic power system could be examined. Three, four and five machine power system models are utilized in this study and its fleeting response to a huge disorder is conferred with the (multi –mode) waving phenomenon.

Multimode oscillations happen in a (multi-machine) power system in the coordinated generating units which have high various inactivity and are broadly linked by utilize transmission lines. These ones vibrations are mods between machines. Depending upon their location in the system, some generators participate in only one oscillation mode while others participate in more than one mode [2].

Speed deviation Δω, and accelerating power ΔPe, are chosen accordingly the inputs to ERANFIS PSS. It is demonstrated by the simulation results that when installed on different machines, the proposed ERANFIS PSS can adjust itself to provide good damping for different oscillation modes, such as the local and inter-area mode. The ERANFIS PSS employed in this test have two inputs. Accelerating power (ΔPe) and speed deviation, Δω for each machine is used the inputs to the stabilizer as shown in Fig. (11). A washout filter is utilized to remove the DC value before speed deviation signal is fed the stabilizer.

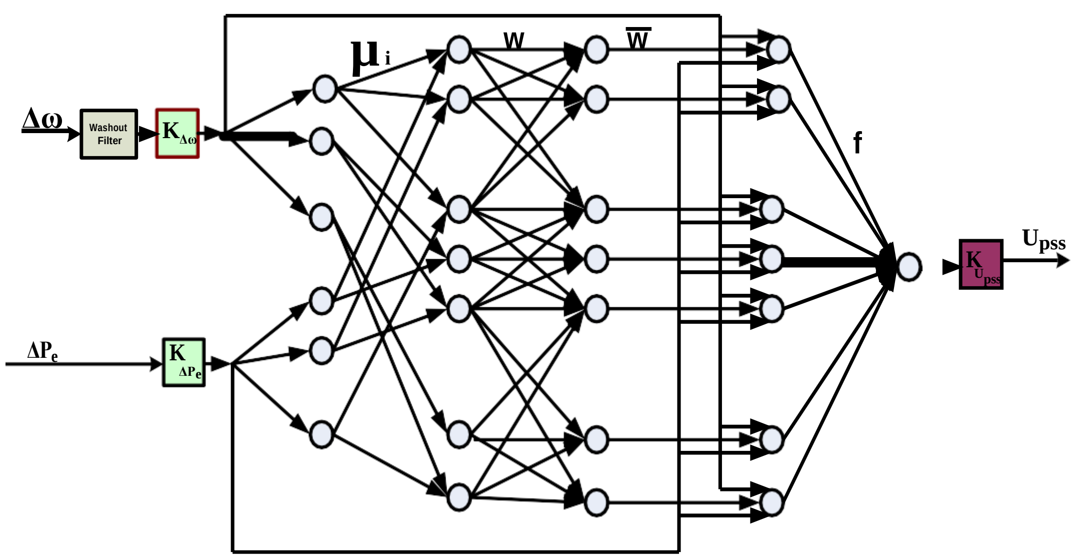


Fig. 11 Structure of ERANFIS PSS used in Multi-machine

The method of gradient descent can be used for tuning the ANFIS's parameters as mansion in chapter three.

(B) Simulation Results of Multi-machine Power System Tests

To verify the performance of the suggested stabilizer, the simulation was carried out on two models of the multi-machine power system supply, two-section of power supply system with 4 machines, and five an endless system of buses for automobiles [16].

In figure (12) shows a system with 4 machines and two areas, which are the generators are placed in two remote areas, and three are not an endless bus in the system. In [16] has been given the specification. The proposed ERANFIS PSS technique is compared with Kundur PSS and CPSS technique which applied at the same system [16]. The proposed ERANFIS PSS technique is compared with Kundur PSS and CPSS technique which applied at the same system [16] in the different tests as follow:

Test-1

A three-phase fault was applied at the middle of transmission line (7-8) between two-areas (Fig.12) and was cleared after 0.08 sec. If PASS isn't put in, the system is unsteady down weighty load, and the system response comparison under CPSS, Kundur PSS and proposed stabilizer (ERANFIS PSS) as follow:

The terminal voltage response of four generators under this test as shown in figure (13), and the rotor sped different between G1 and other generators (G2,G3,G4) under this fault as shown in figures (14) , (15) and (16) respectively. Generators rotor mechanical angle (theta) different between all generators and G4 response is shown in figure (17).

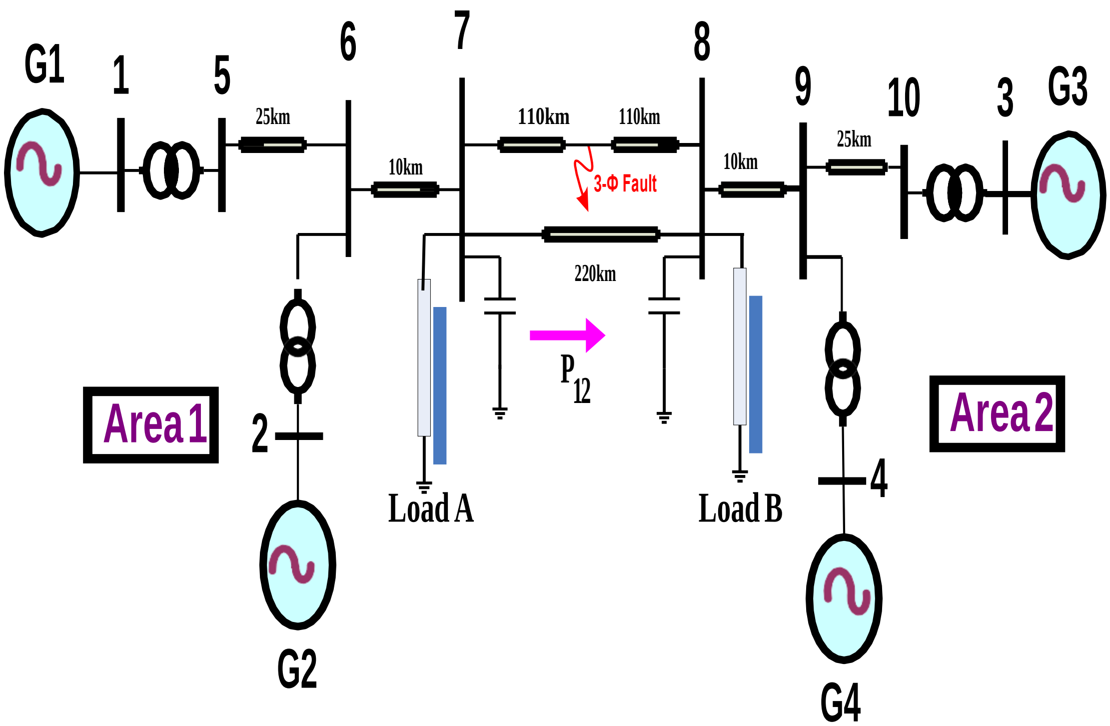
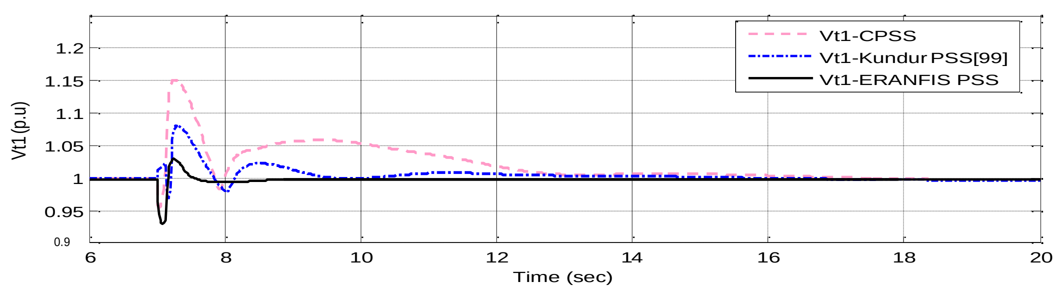
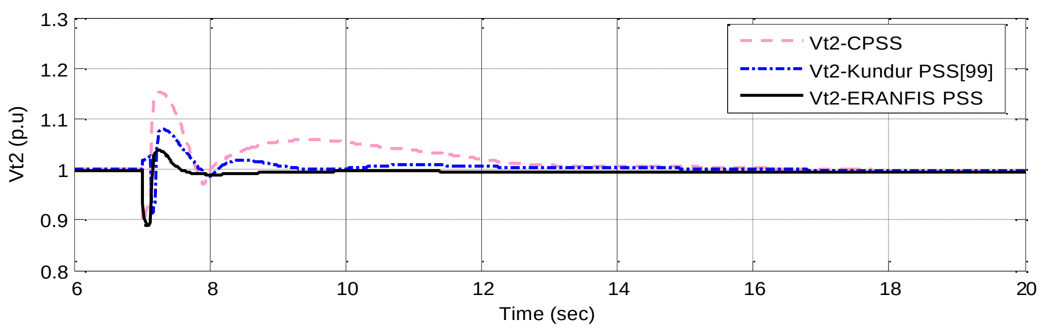


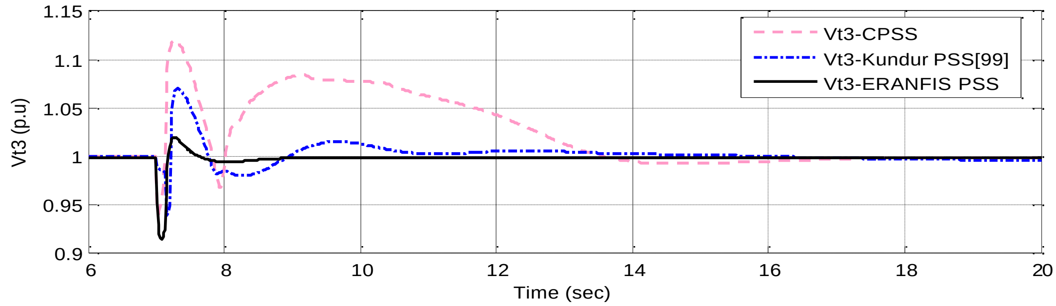
Fig. 12 A single –line Diagram for the Two-Area Four –Machine Power System



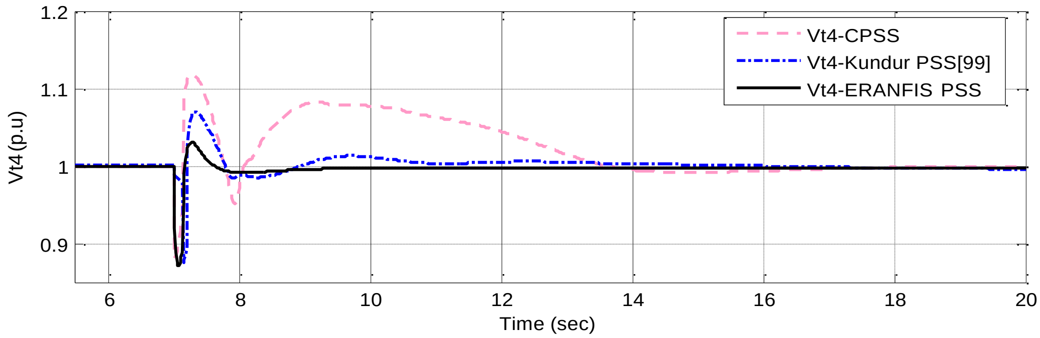
(a)



(b)



(c)



(d)

Fig. 13 Generators Terminal Voltage Response under Test (a) Vt1 (b) Vt2 (c) Vt3 (d) Vt4

VI. CONCLUSION

In this paper, an adaptive neuro-fuzzy power system stabilizer based error reference model (ERANFIS PSS) has introduced. The controller of the system of Surgeon-FLC inference of the first-order is used as a stabilizer. The parameters of the fuzzy inference system (FIS) are refresh in accordance with the reference error model based on the technique of back propagation of a neural network. Scale deviation and acceleration in case of serious malfunctions, like three phase errors. Due to the fact that information about the operating conditions is obtained online, therefore the ERANFIS PSS would work if it is designed properly. In addition, if the scaling element of the) ANFIS(adjusted well, it could be acclimatized to dissimilar systems. The suggested stabilizer has worked on the single-machine and multi-machine. The simulation results has shown the performance of the suggested stabilizer to damping low-repetition vibrations in comparison to traditional properly contagious and Kundur's stabilizer.

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Appendix A

Single-Machine power system

Exciter parameters (IEEE-Type ST3 Model):

$T_A=0$	$V_{IMIN}=-0.2$	Kg=1.0
$T_R=0$	$V_{MAX}=1.0$	$K_M=7.93$
$T_M=0.4$	$V_{MMIN}=0$	$K_A=200$
$T_B=10.0$	$V_{RMAX}=10.0$	$K_P=6.15$
$T_C=1.0$	$V_{Rmin}=-10.0$	$\Theta_P=0o$
$X_L=0.081$	$V_{GMAX}=5.8$	$K_I=0$
$V_{IMAX}=0.2$	$E_{FDMAX}=6.9$	$K_C=0.20$

Stabilizer Type PSS1A (Input :Seed or frequency)

A_1= 0.61 T_3=0.3 V_{STMAX} = 0.05

A_2=0.0017 T_4=0.0 V_{STMIN} = - 0.05

T_1=0.3 T_5= 10

Generator Parameters :

X_I = 0.2 p.u x''_q = 0.242 p.u

Ra=0.0025 p.u T'_{qo} = 0.66 s

Xd = 1.8 p.u T''_{qo} = 0.1 s

X'_d = 1.05 p.u H= 3.2 s

T'_{do} = 1.01 s D=0

T''_{do}=0.053 s Generator base : 200 MVA

X_q = 0.42 p.u

Governor Parameters:

Speed set point = 1.0 p.u

Steady-stat gain (1/R) = 10/3

Ts = 0.1 s

Tc = 0.4 s

T3= 0

T4= 1.25 s

T5= 5.0 s

Appendix B

4-Machine Power System model

1- Generator data

Gen.No	X_d	X'_d	X''_d	T'_{do}	T''_{do}	X_q	X''_q	T''_{qo}	H	D
1	0.2	0.033	0.0264	8.0	0.05	0.19	0.03	0.04	54	0
2	0.2	0.033	0.0264	8.0	0.05	0.19	0.03	0.04	54	0
3	0.2	0.033	0.0264	8.0	0.05	0.19	0.03	0.04	54	0
4	0.2	0.033	0.0264	8.0	0.05	0.19	0.03	0.04	54	0

2- IEEE ST1A type exciter data:

Gen.No	Tr	TC	TB	KA	TA	KF	TF	V_{RMAX}	V_{RMIN}	KC	KLR
1	0.02	1.0	1.0	200	0.02	0	1.0	7	-6.4	0.04	4.54
2	0.02	1.0	1.0	200	0.02	0	1.0	7	-6.4	0.04	4.54
3	0.02	1.0	1.0	200	0.02	0	1.0	7	-6.4	0.04	4.54
4	0.02	1.0	1.0	200	0.02	0	1.0	7	-6.4	0.04	4.54

3-speed-governor /hydro-turbine:

Geng.No	TW	TG	SIGMA	T2	PMAX_fac	PMIN_fac
1	1	0.2	0.05	0	1.1	0.1
2	1	0.2	0.05	0	1.1	0.1
3	1	0.2	0.05	0	1.1	0.1
4	1	0.2	0.05	0	1.1	0.1

4-Network data:

From	To	R	X	B	Remarks
5	6	0.005	0.05	0.075	Line 1
6	7	0.002	0.02	0.03	Line 2
7	8	0.022	0.022	0.033	Line 3
7	8	0.022	0.022	0.033	Line 4
8	9	0.002	0.02	0.03	Line 5
9	10	0.005	0.02	0.075	Line 6
1	5	0.001	0.012	1.00	Transformer
6	2	0.001	0.012	1.00	Transformer
10	3	0.001	0.012	1.00	Transformer
9	4	0.001	0.012	1.00	Transformer