Intelligent AVR and PSS with Adaptive Hybrid Learning Algorithm

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***Abstract*—The paper presents a step-by-step design methodology of an Adaptive Neuro-Fuzzy Inference System (ANFIS) based Automatic Voltage Regulator (AVR) and Power System Stabilizer (PSS) and also demonstrates its performance in a single-machine-infinite-bus and a multi-machine power system through digital simulation. The design employs a zero and a first order Sugeno fuzzy model, whose parameters are tuned off-line through hybrid learning algorithm. This algorithm is a combination of Least Square Estimator and Error Backpropagation method. The performance of this ANFIS-based AVR and PSS in damping both local and inter-area oscillation is then compared with conventional fuzzy AVR and PSS performances. It is found that the damping characteristics of both ANFIS-based AVR and PSS are better than the conventional fuzzy AVR and PSS. The effectiveness of the proposed ANFIS-based AVR and PSS in small-signal stability is thus established.**

***Index Terms*— AVR, PSS, Fuzzy Logic, Adaptive Neuro-Fuzzy Inference System, Sugeno-Fuzzy Model, Hybrid Learning Algorithm**

I. Introduction

In the past decades, with the emergence of large interconnected power systems all over the world, stability has become an important consideration. Power systems often undergo faults, load changes and many other disturbances, which in turn introduce Low Frequency Oscillations (LFO) affecting the maximum power transfer capability limits. In order to restore the terminal voltage instantaneously, a high field current is injected applying high gain Automatic Voltage Regulators (AVR). But, this high gain often introduces negative damping torque to produce sustained oscillations [10]. To mitigate these long-standing low frequency oscillations, Power System Stabilizers (PSS) are used in conjunction with AVR. The action of PSS is to provide a supplemental damping to the rotor oscillations through an electric torque which is in phase with the speed deviation [8]. But, normally the parameters of these conventional AVR and lead-lag PSS are determined at a nominal operating point to give good performance. However, the system dynamic performance may deteriorate when the operating point changes to some extent. Again, in many cases it is observed that, the PSS designed for damping local mode of oscillations, are practically unsuitable for the inter-area mode of oscillations.

To fulfill the above requirements of an excitation control system and to avoid the growing difficulties faced by the conventional control schemes, Artificial Intelligence (AI) is now being widely used. Among AI techniques, fuzzy logic control appears to be the most promising, due to its lower computational burden and robustness [5]. Also, in the design of fuzzy logic controllers, a mathematical model is not required to describe the system under study.

However, in case of fuzzy control, the main problem is that the parameters associated with the membership functions and the rules depend broadly on the intuition of the engineer. To overcome this over-dependence on human intuition, Adaptive Neuro-Fuzzy Inference System (ANFIS) is used. In ANFIS, rather than choosing the parameters associated with a given membership function arbitrarily, these parameters are chosen so as to tailor the membership functions to a set of input/output data in order to account for these types of variations in the data values. This learning method is similar to that of neural networks. In this paper, zero and first order Sugeno fuzzy models with hybrid-learning algorithm are used. This algorithm is a combination of backpropagation for the parameters associated with the input membership function and least squares estimation for the parameters associated with the output membership function. The parameters associated with the membership functions and rules change through the learning process. The computation of these parameters, or their adjustment, is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. Once the gradient vector is obtained, an optimization routine is applied in order to adjust the parameters so as to reduce the sum of the squared difference between actual and desired outputs.

The objective of this paper is to introduce ANFIS-based AVR and PSS in small-signal stability with Hybrid Learning Algorithm. In the following sections, brief introductions to

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Sugeno fuzzy model, ANFIS architecture and hybrid learning are given. Then the design process of ANFIS-based AVR and PSS is elaborated. Finally, in the results section, it is shown that the designed AVR and PSS can satisfactorily substitute the conventional fuzzy AVR and PSS in single-machine and multi-machine operation.

II. SUGENO FUZZY MODEL

Unlike Mamdani model, Sugeno output membership functions are either linear or constant. If a fuzzy system has two inputs *x* and *y* and one output *f*, then for a first order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is as follows:

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

Rule 1: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

For a zero-order Sugeno model, the output level is a constant ($p_i = q_i = 0$)

The output level f_i of each rule is weighted by the firing strength w_i of the rule. For example, for an AND rule with *Input 1 = x* and *Input 2 = y*, the firing strength is

$$w_i = AND\ method\ (A_1(x), B_1(y))$$

Where A_1 and B_1 are the membership functions for *Input 1* and *Input 2* respectively. The final output of the system is the weighted average of all rule outputs, computed as

$$\text{Final Output} = \frac{\sum_{i=1}^{n} w_i f_i}{\sum_{i=1}^{n} w_i}$$

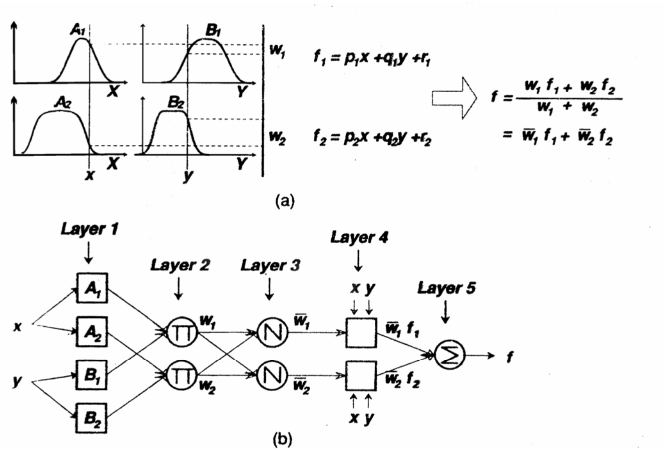

Fig. 1 (a) A two-input first-order Sugeno fuzzy model with two rules; (b) Equivalent ANFIS architecture [9]

III. ANFIS ARCHITECTURE

Fig.-1(a) illustrates the reasoning mechanism for the Sugeno model discussed above while the corresponding ANFIS architecture [6] is as shown in Fig.-1(b), where nodes of the same layer have similar functions. The output of i^{th} node in layer l is denoted as $O_{l,i}$.

Layer 1: Every node *i* in this layer is an adaptive node with a node function

$$O_{l,i} = \mu_{A_i}(x), \quad \text{for i = 1, 2, or}$$
$$O_{l,i} = \mu_{B_{i-2}}(y), \quad \text{for i = 3,4,}$$

Where *x* (or *y*) is the input to node *i* and A_i (or B_{i-2}) is a linguistic label ("small" or "large") associated with the node. Here the membership function for *A* (or *B*) can be any parameterized membership function. In this paper, generalized Gaussian membership function is taken as follows

$$\mu_A(x) = \exp[-(\frac{x - c_i}{a_i})^2]$$

Where $\{c_i, a_i\}$ is the parameter set. These are called premise parameters.

Layer 2: Every node in this layer is a fixed node labeled $\prod$, whose output is the product of all the incoming signals.

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad \text{i=1,2.}$$

Layer 3: Here, the i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of all rule's firing strengths.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad \text{i=1,2.}$$

Layer 4: Every node *i* in this layer is an adaptive node with a node function

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i\text{x}+q_i\text{y}+r_i),$$

Where $\bar{w}_i$ is a normalized firing strength from layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set of the node. These parameters are referred to as consequent parameters.

Layer 5: The single node in this layer is a fixed node labeled $\sum$, which computes the overall output as the summation of all incoming signals:

$$O_{5,1} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

IV. HYBRID LEARNING ALGORITHM

The Hybrid Learning Algorithm [9] is a combination of least square and backpropagation method. In the least square method, the output of a model *y* is given by the parameterized expression

$$y = \theta_1 f_1(\text{u}) + \theta_2 f_2(\text{u}) + ... + \theta_n f_n(\text{u}) \qquad \text{(i)}$$

Where $\text{u} = [u_1, ..., u_n]^T$ is the model's input vector, $f_1, \ldots\ldots, f_n$ are known functions of *u*, and $\theta_1, ..., \theta_n$ are unknown parameters to be optimized. To identify these unknown parameters θ_i, usually a training data set of data pairs $\{(u_i, y_i), i = 1, ..., m\}$ is taken; substituting each data pair in equation (i) a set of linear equations is obtained, which can be written as

$$A\theta = y \qquad \text{(ii)}$$

in matrix form. Where A is a $m \times n$ matrix, θ is an $n \times 1$ unknown parameter vector and *y* is an $m \times 1$ output vector.

Since generally *m>n*, instead of exact solution of the equation (ii) an error vector e is introduced to account for the modeling error, as

$$A\theta + e = y \qquad \text{(iii)}$$

and searched for $\theta = \hat{\theta}$ which minimizes sum of squared error

$$E(\theta) = \sum_{i=1}^{m} (y_i - a_i^T \theta)^2 = e^T e \qquad \text{(iv)}$$

$E(\theta)$ is called the objective function. The squared error in equation (iv) is minimized when $\theta = \hat{\theta}$, called Least Squares Estimator (LSE) that satisfies the normal equation

$$A^T A \hat{\theta} = A^T y \qquad \text{(v)}$$

If $A^T A$ is non singular, $\hat{\theta}$ is unique and is given by

$$\hat{\theta} = (A^T A)^{-1} A^T y \qquad \text{(vi)}$$

In case of Backpropagation learning rule the central part concerns how to recursively obtain a gradient vector in which each element is defined as the derivative of an error measure with respect to a parameter.

Assuming that a given feedforward adaptive network has *L* layers and layer *l* has N(*l*) nodes, then the output function of node *i* in layer *l* can be represented as $x_{l,i}$ and $f_{l,i}$ respectively. Node function $f_{l,i}$:

$$x_{l,i} = f_{l,i}(x_{l-1,1}, \ldots\ldots, x_{l-1,N(l-1)}, \alpha, \beta, \gamma, \ldots.), \qquad \text{(vii)}$$

where α, β, γ, etc. are the parameters of this node.

Assuming that the given training data set has P entries, an error measure can be defined for the p^{th} $(1 \le p \le P)$ entry of the training data set as the sum of squared errors:

$$E_p = \sum_{k=1}^{N(L)} (d_k - x_{L,k})^2, \qquad \text{(viii)}$$

where d_k is the k^{th} component of the p^{th} desired output vector and $x_{L,k}$ is the k^{th} component of the actual output vector produced by presenting the p^{th} input vector to the network. The task here is to minimize an overall error measure, which is defined as $E = \sum_{p=1}^{P} E_p$.

To use steepest descent to minimize the error measure, first the gradient vector is to be obtained. The basic concept in calculating the gradient vector is to pass a form of derivative information starting from the output layer and going backward layer by layer until the input layer is reached. That is why the process is called 'backpropagation'.

The error signal $\in_{l,i}$ is defined as

$$\in_{l,i} = \frac{\partial E_p}{\partial x_{l,i}} \qquad \text{(ix)}$$

(This is actually ordered derivative and is different from ordinary partial derivative.)

For i^{th} output node (at layer L)

$$\in_{L,i} = \frac{\partial E_p}{\partial x_{L,i}} \qquad \text{(x)}$$

$$\therefore \in_{L,i} = -2(d_i - x_{L,i}) \qquad \text{(xi)}$$

For the internal node at the i^{th} position of layer *l*, the error signal can be derived iteratively by the chain rule:

$$\in_{l,i} = \frac{\partial E_p}{\partial x_{l,i}} = \sum_{m=1}^{N(l+1)} \frac{\partial E_p}{\partial x_{l+1,m}} \frac{\partial f_{l+1,m}}{\partial x_{l,i}}$$
$$= \sum_{m=1}^{N(l+1)} \in_{l+1,m} \frac{\partial f_{l+1,m}}{\partial x_{l,i}} \qquad \text{(xii)}$$

The gradient vector is defined as the derivative of the error measure with respect to each parameter. If α is a parameter of the i^{th} node at layer *l*, we have

$$\frac{\partial E_p}{\partial \alpha} = \frac{\partial E_p}{\partial x_{l,i}} \frac{\partial f_{l,i}}{\partial \alpha} = \in_{l,i} \frac{\partial f_{l,i}}{\partial \alpha} \qquad \text{(xiii)}$$

The derivative of the overall error measure E with respect to α is

$$\frac{\partial E}{\partial \alpha} = \sum_{p=1}^{P} \frac{\partial E_p}{\partial \alpha} \qquad \text{(xiv)}$$

Accordingly, for simplest steepest descent without line minimization, the update formula for generic parameter α is

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \qquad \text{(xv)}$$

in which η is the learning rate. So, for parameter α it may be written that,

$$\alpha_{new} = \alpha_{old} + \Delta\alpha$$
$$= \alpha_{old} - \eta \frac{\partial E}{\partial \alpha} \qquad \text{(xvi)}$$

In this type of learning, the update formula for parameter α is based on the above equations and the update action occurs only after the whole set of training data pair is presented. This process of presentation of whole set of training data pair is called epoch. That is, after each epoch the update takes place [9].

Now, It is assumed that *'S'* is the total set of parameters and *'S_1'* and *'S_2'* are the sets of input and output parameters respectively. For hybrid learning algorithm, each epoch consists of a forward pass and a backward pass. In the *forward pass*, when a vector of input data pair is presented, the node outputs of the system are calculated layer by layer. This process continues till the corresponding row in the matrices A and y of equation (ii) are obtained. The process is repeated for all the training data pair to form the matrices A and y completely. Then the output parameters of set S_2 are calculated according to the equation (vi) of least square method. After the identification of output parameters the error measure for each training data pair is to be calculated. The derivative of those error measures with respect to each node output are calculated following the equations (x) and (xii). Thus the error signal is obtained. In the *backward pass*, these error signals propagate from the output end towards the input end. The gradient vector is found for each training data entry. At the end of the backward pass for all training data pairs, the input parameters in set S_1 are updated by steepest descent method as described earlier. The update formula followed here is given by equation (xvi).

V. DESIGN OF ANFIS BASED AVR AND PSS

A step-by-step method of designing ANFIS-based AVR is first presented as follows:

a) <u>Choice of input variable:</u> In this step it is decided which state variables representative of system dynamic performance must be taken as the input signals to the controller. In this paper, deviation of terminal voltage (e) and its derivative ($\dot{e}$) are taken as input signals of the ANFIS-based AVR.

b) <u>Choice of linguistic variables:</u> The linguistic values may be viewed as labels of fuzzy sets [2]. In this paper, seven linguistic variables for each of the input variables are used to describe them. These are, **LP** (Large Positive), **MP** (Medium Positive), **SP** (Small Positive), **ZE** (Zero), **SN** (Small Negative), **MN** (Medium Negative), **LN** (Large Negative).

c) <u>Choice of membership functions:</u> In this design, Gaussian membership functions are used to define the degree of membership of the input variables.

d) <u>Choice of fuzzy model:</u> A zero order Sugeno fuzzy model is chosen for ANFIS-based AVR.

e) <u>Preparation of training data pair:</u> In preparing the training data pair, the data should be representative of different kinds of disturbance situations, such that the designed AVR can be used for highest flexibility and robustness. In this paper, the input and output training data pair for the ANFIS-based AVR are prepared by simulating the power system with conventional AVR under a broad range of small and large disturbances and for each run the conventional AVR is tuned to give best performance.

f) <u>Optimization of unknown parameters:</u> Using the training data matrix, the unknown parameters of the Gaussian input membership functions (center (c_i) and spread (a_i)) and the output parameters of each rule of zero order Sugeno fuzzy model are optimized. Initially, it is assumed that the input membership functions are symmetrically spaced over the entire universe of discourse. Accordingly some initial values for the center and the spread of each input membership function are assumed, whereas, in case of output for each rule, all initial values are assumed to be zero. Then, the input parameters are optimized by error backpropagation algorithm and the output constants are optimized by least square method. The tuned AVR thus obtained is used in the test systems to obtain a stable output.

Now, in case of design of ANFIS based PSS, the same procedure is adopted except the following differences:

1) The input variables are rotor speed deviation ($\Delta\omega$) and acceleration ($\Delta\dot{\omega}$) respectively and the output is a voltage signal, V_{PSS}. Speed deviation and accelerating power deviation can also be chosen as input signal [1].

2) Unlike AVR model, the PSS model is a first order Sugeno fuzzy model where p_i and q_i are non-zero.

VI. TEST SYSTEMS

Fig.-2 shows the single-machine-infinite-bus system (Test system 1) while Fig.-3 shows the two-area four-machine system (Test System 2). Both the systems are simulated in MATLAB SIMULINK platform.

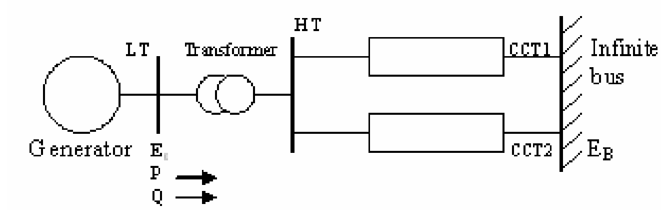

Fig. 2 Single Machine Infinite Bus System (Test System 1)

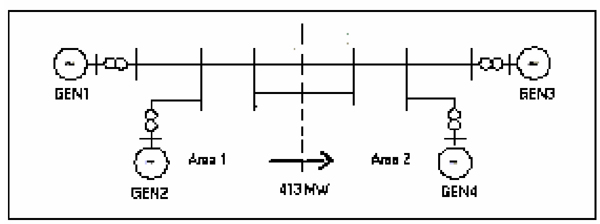

Fig. 3 Two-Area Four-Machine System (Test System 2)

Test System 1 represents a thermal generating station consisting of four 555 MVA, 24 kV, 60 Hz units connected to an infinite bus through a step up transformer (reactance 0.15 p.u.) and two parallel transmission lines with reactance 0.5 and 0.93 p.u. respectively. The small signal stability characteristics are analyzed about the steady state operating conditions following the loss of tie line 2. The post fault system condition, network reactance and other circuit parameters are such that, when the small signal stability characteristics of the system is analyzed about the steady-state operating condition the values of the K-constants are calculated as follows:

$K_1 = 0.7643$, $K_2 = 0.8649$, $K_3 = 0.3230$, $K_4 = 1.4187$
$K_5 = -0.1463$, $K_6 = 0.4168$, $T_R = 0.02$ s
Conventional AVR gain K_A=200
Conventional PSS parameters:
Kstab = 9.5, Tw = 1.4 s, $T_1 = 0.154$ s, $T_2 = 0.033$ s

Test System 2 comprises four identical 20 kV, 900MVA generators and each two of them constitute one area. The two areas are linked by two 230 kV lines. The generators are employed with fast, static AVR [7]. The parameters for generator, AVR and conventional PSS are given below:

Generator data:

$X_d = 1.8$, $X_d^{/} = 0.3$, $X_d^{//} = 0.25$, $X_q = 1.7$, $X_q^{/} = 0.55$, $X_q^{//} = 0.25$, $X_l = 0.2$ (all data in p.u.)

$T_{d0}^{/} = 8$, $T_{d0}^{//} = 0.03$, $T_{q0}^{/} = 0.4$, $T_{q0}^{//} = 0.05$, (all data in sec.)

Rs = 0.0025 (p.u.), H = 6.5 (sec.) for machines 1 and 2,

H= 6.175 (sec.) for machines 3 and 4.

Conventional AVR data:

Tr = 0.02 (sec.), Ta = 0.001(sec.), Ka = 200.

Conventional PSS data:

Kstab = 20,

Tw = 10, $T_1 = 0.05$, $T_2 = 0.02$, $T_3 = 3$, $T_4 = 5.4$ (all data in sec.)

VII. RESULTS

In order to study the performance of ANFIS based AVR, test system 1 is first simulated with conventional AVR under wide range of disturbance conditions and then for each run, the conventional AVR is most efficiently tuned. Thus, a set of input-output training data pair is obtained. Now, the initial input membership function (Gaussian) parameters are taken in such a way, that they are evenly spaced within the universe of discourse [3]. Here, in case of ANFIS no scaling or normalization [4] is necessary. The fuzzy AVR is assumed to be zero order Sugeno model, where all the output constant terms (r_i) are initially taken to be zero. The unknown parameters are then optimized. Just as an example of successful optimization, Table-1 is given to show the values of the centres (c_i) and spreads (a_i) of the membership functions of input 1 before and after optimization. The output constants of the zero order Sugeno model are also optimized in a similar manner.

TABLE 1

MEMBERSHIP FUNCTION PARAMETERS BEFORE AND AFTER OPTIMIZATION FOR ANFIS AVR

		Before	After
LN	a_i	0.8366	0.1284
	c_i	-0.1067	-0.11
MN	a_i	0.8366	0.1114
	c_i	0.09027	0.06561
SN	a_i	0.8366	0.1029
	c_i	0.2873	0.29
ZE	a_i	0.8366	0.1098
	c_i	0.4843	0.4746
SP	a_i	0.8366	0.08301
	c_i	0.6813	0.6799
MP	a_i	0.8366	0.09175
	c_i	0.8733	0.8711
LP	a_i	0.8366	0.08121
	c_i	1.075	1.076

Now, the performances of this ANFIS based AVR for single-machine system in small signal stability is demonstrated by Fig.-4 and Fig.-5. Comparing it with ordinary fuzzy AVR, it is found that the terminal voltage characteristics is almost as good as the fuzzy AVR, whereas the rotor angle oscillation damps a little earlier in case of ANFIS based AVR that ordinary fuzzy AVR.

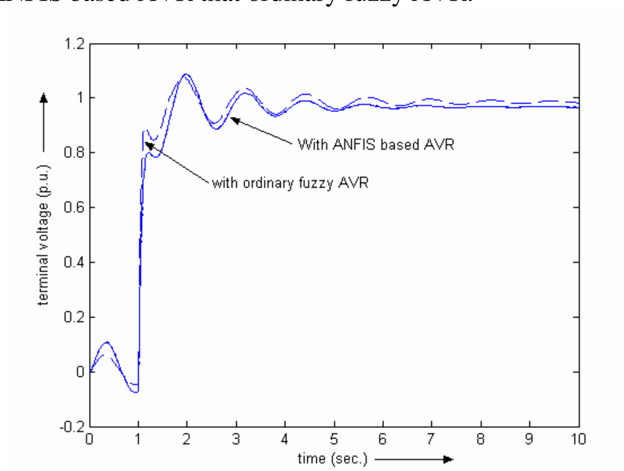

Fig. 4 Terminal voltage characteristics with ANFIS-based AVR and Conventional Fuzzy AVR

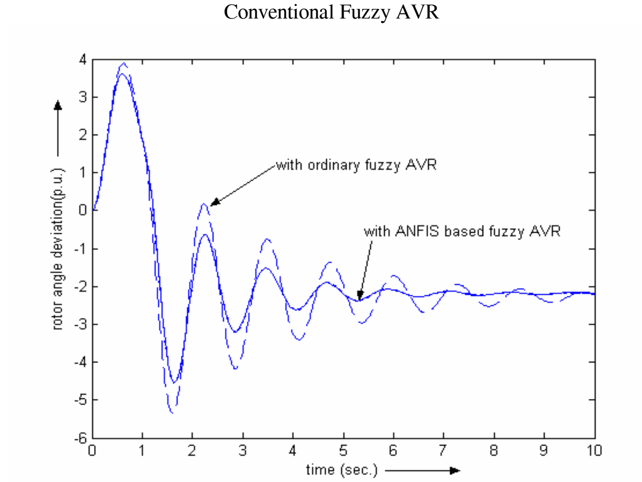

Fig. 5 Rotor angle characteristics with ANFIS-based AVR and Conventional Fuzzy AVR

To study the performance of the ANFIS based PSS in small signal stability, first test system 1 is taken. The unknown parameters are tuned in the same way as in case of AVR. Now, running the optimization routine, it is found that there is no significant change in the parameters of the Gaussian membership function initially taken, but the output constants (p_i, q_i and r_i) of the first order Sugeno model for all the 49 rules are obtained.

The PSS is now connected to the single-machine system and simulated. The rotor angle characteristic of the system with this PSS is then compared to ordinary fuzzy PSS. As shown in Fig.-6, the performance of ANFIS based PSS is much better than the ordinary PSS.

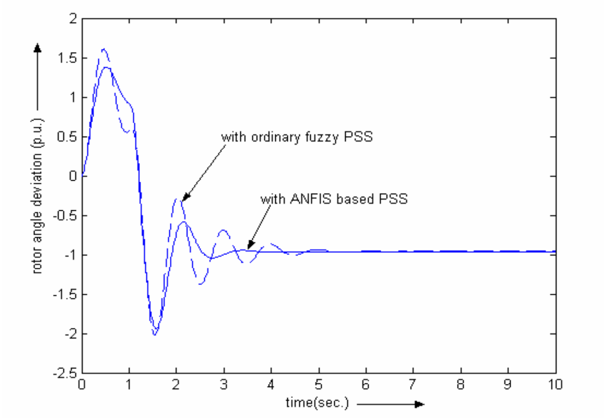

Fig. 6 Rotor Angle Deviation in Test System 1 with ANFIS-based PSS and Conventional Fuzzy PSS

The performance of the ANFIS-based PSS is then tested for Test System 2. The system is simulated for a 5% magnitude pulse in mechanical power input to the machine 1. The performances of the PSS are shown in Fig.-7 and Fig.-8. It is found that the proposed ANFIS-based PSS is performing better than the conventional fuzzy PSS in case of damping local oscillations like rotor angle deviation of machines 1 w.r.t. machine 4, as well as for inter-area oscillations.

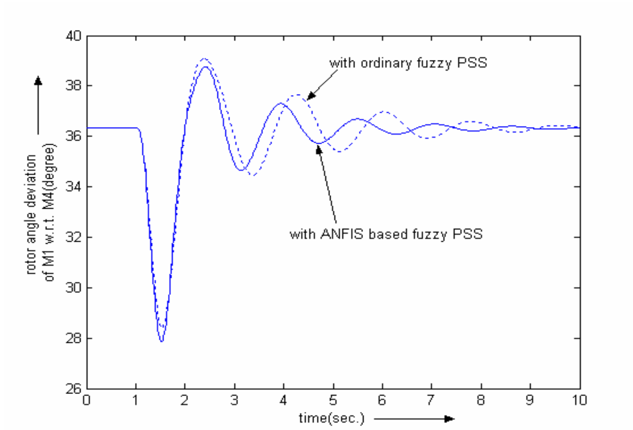

Fig. 7 Rotor angle deviation of Machine1 w.r.t. Machine 4 in Test System 2 with ANFIS-based PSS and ordinary fuzzy PSS

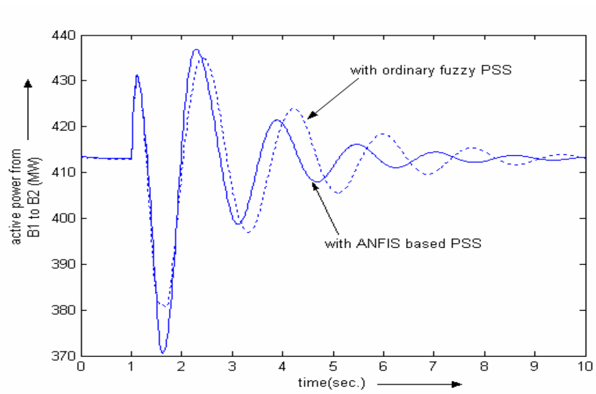

Fig. 8 Active Power Transfer From Area 1 To Area 2 in Test System 2 with ANFIS-based PSS and Conventional Fuzzy PSS

Now, the same system is simulated with 10% magnitude pulse in mechanical power input to the machine 1. The speed and rotor angle deviation of machine 1, the positive sequence voltage at bus1 and the inter area power transfer are shown in Fig.-9, Fig.-10, Fig.-11 and Fig.-12 respectively. From the figures it is clearly found that for larger disturbance, the ANFIS based PSS damps the oscillations much quicker, whereas the ordinary fuzzy PSS fails to restore the stability within a considerable time.

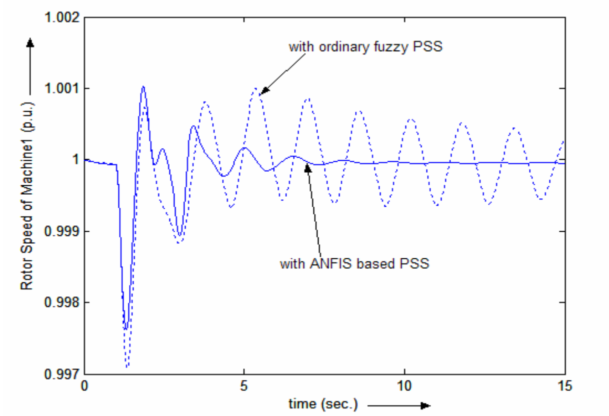

Fig. 9 Rotor angle deviation of Machine1 w.r.t. Machine 4 with ANFIS-based PSS and ordinary fuzzy PSS

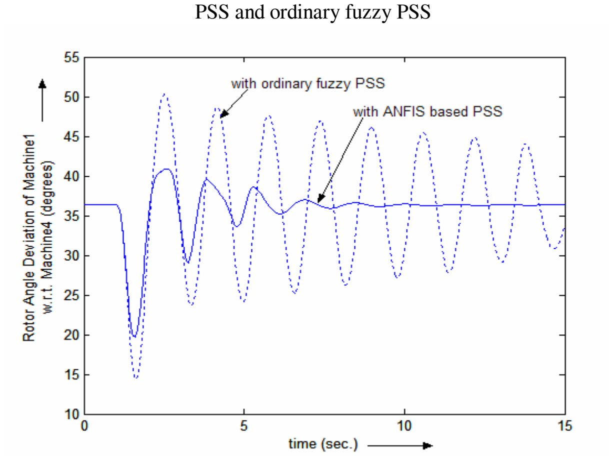

Fig. 10 Rotor speed of Machine1 w.r.t. Machine 4 with ANFIS-based PSS and ordinary fuzzy PSS

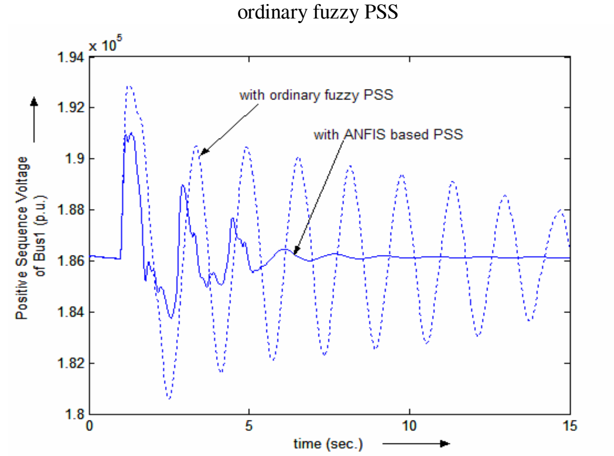

Fig. 11 Positive sequence voltage of bus 1 with ANFIS-based PSS and ordinary fuzzy PSS

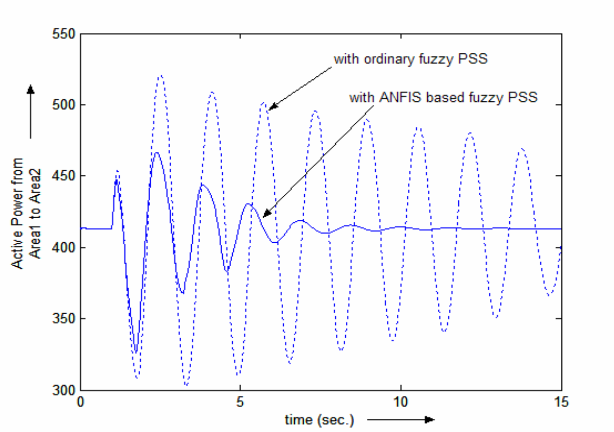

Fig. 12 Active Power Transfer From Area 1 To Area 2 with ANFIS-based PSS and Ordinary Fuzzy PSS

Hence, it is found; that the role of designed ANFIS-based PSS is satisfactory and is superior to conventional fuzzy PSS. So, it can be concluded that a better fuzzy AVR and PSS can be obtained with ANFIS, which has less dependence on human intuition.

VIII. CONCLUSION

The paper highlights a systematic approach for designing an ANFIS-based Automatic Voltage Regulator and Power System Stabilizer with the application of Hybrid Learning Algorithm. These ANFIS based AVR and PSS overcome the limitation of a conventional fuzzy AVR and PSS which are over-dependent on human intuition. So, the ANFIS based AVR and PSS achieves more flexibility in operation with wider range of disturbances. The performance of the proposed AVR and PSS is observed here with different grades of small disturbances and is compared with the conventional fuzzy AVR and PSS. A good dynamic performance is obtained, which proves its superiority in small signal stability of power system.

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