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# Research methods for power system stability using Adaptive Neural Fuzzy Inference Systems

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**Abstract:** The performance of the Automatic Voltage Regulate (AVR) and the Power System Stability (PSS) methods may be degraded stability of the power system. This paper presents an Adaptive Neural Fuzzy Inference Systems (ANFIS) algorithm for stability of the power system, we use an Adaptive Network based Fuzzy Interference System architecture extended to response with multivariable systems. By using a hybrid learning method, the suggested ANFIS can setting structure diagram input - output based on both human knowledge and stipulated input-output data pairs. Simulation results present the convergence of the algorithm is improved.

**Keywords:** AVR, PSS, ANFIS

## 1. Introduction

In power systems, the electromechanical oscillations of the generators may adversely affect. Thus, using the power system stabilizer PSS controllers is necessary. It will damp the electromechanical oscillations in power systems. The plants of linear models at each operating point are different. The proposed PSS based primarily on a transfer function and a linear model of the plant has been widely used [1, 2, 3].

However, the feature of the power systems has dynamic and highly nonlinear. Therefore, the performance of PSS can degrade under variations of the nonlinear characteristics of the plant.

In recent years researchers used neural - fuzzy techniques to control complex systems utilizing solely the input-output data sets. Meanwhile, fuzzy control technique requires human knowledge and experience to set the IF – THEN rules. This deficiency can be overcome by combining the neural networks and fuzzy logic, the proposed ANFIS with rule-based of controllers has shown promising results [ 5, 6].

The viewpoint proposed here which is Adaptive Neural Fuzzy Inference Systems is used to solve the problems mentioned above. We use ANFIS replace the conventional control method to solve the performance concerns. In this study, a first step is taken towards systematic analysis using ANFIS algorithm.

This paper refers to a controller using Adaptive Neural Fuzzy Inference Systems to replace the power system stabilizer (PSS). This is one control algorithm is used widely in the field of automatic control which is effective for the nonlinear of plants. Adaptive Neural Fuzzy Inference Systems algorithm is used for power system operation which excitation system of the generator will be automatically adjusted to limit disturbance. In there, research issues set for controller parameters is very important, it determines the performance characteristics of the system generator.

The remainder of the paper is organized as follows. Section II describes Mathematical model of the system to synchronize generators. In section III, The Adaptive Neural Fuzzy Inference Systems (ANFIS) in Small-signal Stability for Power System is presented. Section IV presents simulation results. The conclusions are given in section V.

## 2. Mathematical Model of the System to Synchronize Generators

For small-signal stability analysis, dynamic modeling is required for the major components of the power system. It includes the synchronous generator, excitation system, automatic voltage regulator (AVR), etc. The model shown in

Figure 1 is used to obtain the linearized dynamic model [13].

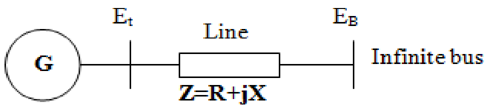


***Figure 1.*** *Single machine connected to a large system through transmission lines*

The governing dynamic equations of the system [9] are shown as in (1).

$$\begin{cases} \Delta T_e = K_1\Delta\delta + K_2\Delta\psi_{fd} \\ \Delta\psi_{fd} = \dfrac{K_3}{1+pT_3}\left[\Delta E_{fd} - K_4\Delta\delta\right] \\ \Delta E_t = K_5\Delta\delta + K_6\Delta\psi_{fd} \\ p\Delta\omega_r = \dfrac{1}{2H}\left(\Delta T_m - K_S\Delta\delta - K_D\Delta\omega_r\right) \\ p\Delta\delta = \omega_0\Delta\omega_r \end{cases} \tag{1}$$

Where

KS is synchronizing torque coefficient in pu torque/rad

KD is damping torque coefficient in pu torque/pu speed deviation

H is inertia constant in (MW-Sec/MVA)

$\Delta\omega_r$ is speed deviation in $pu = (\omega_r - \omega_0)/\omega_0$

$\Delta\delta$ is rotor angle deviation in elec. rad

$\omega_0$ is rated speed in elec. rad/s $= 2\pi f_0$

The coefficients K1 ->K6 depend on the parameters of the grid and the power system voltage.

$$K_1 = \left.\frac{\Delta T_e}{\Delta\delta}\right]_{\psi_{fd}=\psi_{fd0}} = n_1(\psi_{ad0} + L_{aqs}i_{d0}) - m_1(\psi_{aq0} + L'_{ads}i_{q0})$$

$$K_2 = \left.\frac{\Delta T_e}{\Delta\psi_{fd}}\right]_{\delta=\delta_0} = n_2(\psi_{ad0} + L_{aqs}i_{d0}) - m_2(\psi_{aq0} + L'_{ads}i_{q0}) + \frac{L'_{ads}}{L_{fd}}i_{q0}$$

$$K_3 = \frac{L_{fd}}{L_{adu}}\left[\frac{1}{1-(L'_{ads}/L_{fd}) + m_2L'_{ads}}\right]$$

$$K_4 = \frac{m_1L'_{ads}}{L_{fd}L_{adu}}$$

$$K_5 = \frac{u_{d0}}{U_{t0}}\left[-R_am_1 + X_dn_1\right] + \frac{u_{q0}}{U_{t0}}\left[-R_an_1 + X'_dm_1\right]$$

$$K_6 = \frac{u_{d0}}{U_{t0}}\left[-R_am_2 + X_dn_1\right] + \frac{u_{q0}}{U_{t0}}\left[-R_an_2 - X'_dm_2 + \frac{L'_{ads}}{L_{fd}}\right]$$

On the other hand, excitation system is used ST1A which is synthesized in the form of small disturbance in the literature [7, 9, 11]:

$$\Delta E_{fd} = \frac{K_A}{1+sT_A}(-\Delta U_1) \tag{2}$$

Therefore, the model synthesis of linear systems has been derived from power system disturbances as Figure 2.

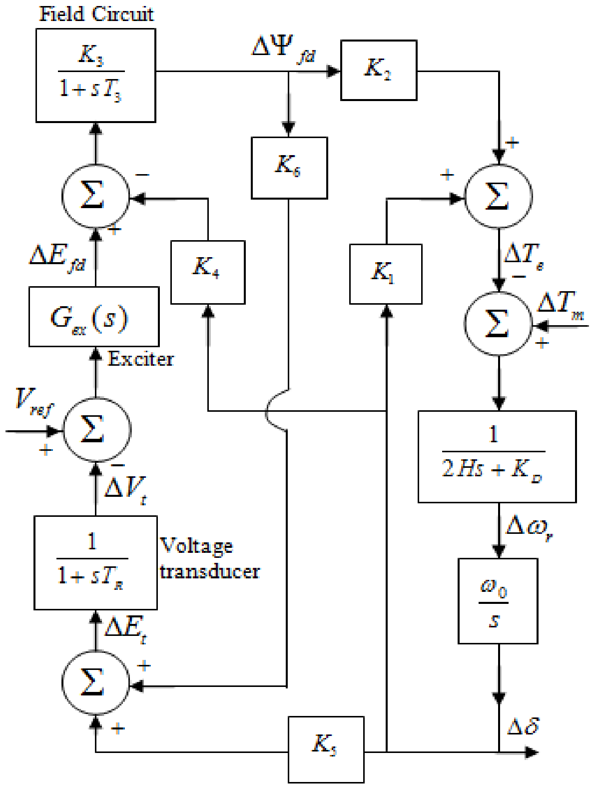


***Figure 2.*** *Block diagram representation with Exciter and AVR.*

## 3. The Adaptive Neural Fuzzy Inference Systems (ANFIS) In Small-Signal Stability for Power System

The Adaptive Neural Fuzzy Inference Systems is a kind of neural network which is based on Takagi–Sugeno fuzzy inference system. Since it integrates both neural networks and fuzzy logic principles, it has ability to capture the advantages of both in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that it is capable of learning to approximate nonlinear functions [10]. Hence, ANFIS is regarded to be a universal estimator.[8]

In this section, we propose a class of adaptive networks which are functionally equivalent to fuzzy inference systems. The proposed architecture this is called ANFIS, standing for Adaptive Neural Fuzzy Inference Systems. We describe how to analyse the parameter set in order to apply the hybrid learning rule. Besides, we demonstrate how to apply the Stone-Weierstrass theorem to ANFIS will be simplified [4, 5]

Fuzzy if-then rules and how the radial basis function network relate to this kind of simplified ANFIS

For simplicity, we assume the fuzzy inference system under consideration has two inputs $x = \Delta\omega$ and $y = \Delta Pe$ and one output f. Suppose that the rule base includes two fuzzy if-then rules of Takagi and Sugeno's type [6, 10].

In this study using 5 set of fuzzy rule, such as:

$$Rule\,1: if\;\; x\;\; is\; A_1\; and\; y\; is\; B_1, then\; f_1 = p_1x + q_1y + r_1,$$
$$Rule\,2: if\;\; x\;\; is\; A_2\; and\; y\; is\; B_2, then\; f_2 = p_2x + q_2y + r_2$$
$$Rule\,3: if\;\; x\;\; is\; A_3\; and\; y\; is\; B_3, then\; f_3 = p_3x + q_3y + r_3$$
$$Rule\,4: if\;\; x\;\; is\; A_4\; and\; y\; is\; B_4, then\; f_4 = p_4x + q_4y + r_4$$
$$Rule\,5: if\;\; x\;\; is\; A_5\; and\; y\; is\; B_5, then\; f_5 = p_5x + q_5y + r_5.$$

For the training of the network, there is a forward pass and a backward pass. We now look at each layer in turn for the forward pass. The forward pass propagates the input vector through the network layer by layer. In the backward pass, the error is sent back through the network in a similar manner to back-propagation.

Then the fuzzy reasoning is illustrated in Figure 3. And the corresponding equivalent ANFIS architecture is in as Figure4.

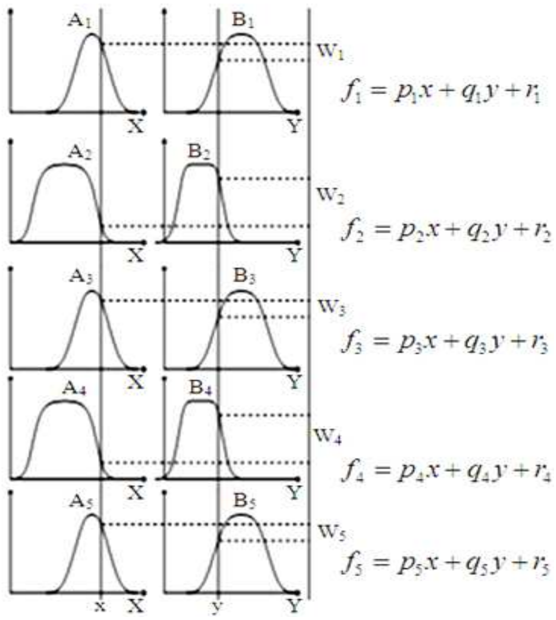


***Figure 3.*** *Fuzzy reasoning*

The node functions in the same layer are of the same function family as described below:

- Layer 1: Every node in this layer is a square node with a node function.

$$O_i^j = \mu_{A_j}(x) \tag{3}$$

Where: $i = 1 \div 2$, $j = 1 \div 5$, x is the input to node i and $A_j$ is the linguistic label (small , large, etc.); associated with this node function. In other words $O_i^j$ is the membership function of $A_j$, and it specifies the degree to which the given x satisfies the quantifier $A_j$.

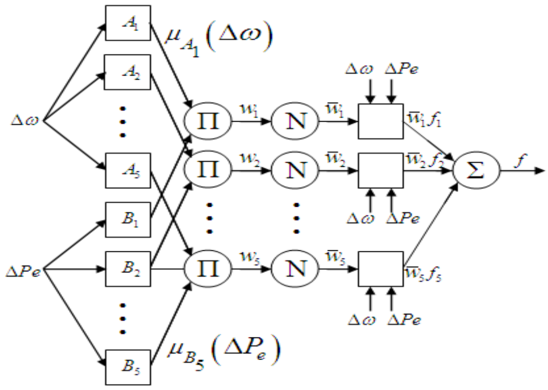


***Figure 4.*** *ANFIS architecture*

In this study we choose (3) to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as (4) and (5).

$$\mu_{A_j}(x) = \mu_{A_j}(\Delta\omega) = \frac{1}{1 + \left|\dfrac{\Delta\omega - c_{ij}}{a_{ij}}\right|} \tag{4}$$

$$\mu_{B_j}(x) = \mu_{A_j}(\Delta P_e) = \frac{1}{1 + \left|\dfrac{\Delta P_e - c_{ij}}{a_{ij}}\right|} \tag{5}$$

Where $\{a_{ij}, b_{ij}, c_{ij}\}$ is the parameter set. As the values of these parameters change, the Bell-shaped functions vary accordingly, thus exhibiting various forms of membership functions on linguistic label $A_j$, $B_j$. Parameters in this layer are referred to as premise parameters.

- Layer 2: Every node in this layer is a circle node labeled II which multiplies the incoming signals and sends the product out, as in (6).

$$w_j = \mu_{A_j}(x).\mu_{A_j}(y) = \mu_{A_j}(\Delta\omega).\mu_{B_j}(\Delta P_e) \tag{6}$$

$$w_1 = \mu_{A_1}(\Delta\omega).\mu_{B_1}(\Delta P_e)$$

$$w_2 = \mu_{A_2}(\Delta\omega).\mu_{B_2}(\Delta P_e)$$

$$w_3 = \mu_{A_3}(\Delta\omega).\mu_{B_3}(\Delta P_e)$$

$$w_4 = \mu_{A_4}(\Delta\omega).\mu_{B_4}(\Delta P_e)$$

$$w_5 = \mu_{A_5}(\Delta\omega).\mu_{B_5}(\Delta P_e)$$

Each node output represents the firing strength of a rule, (In fact, other T-norm operators that perform generalized AND can be used as the node function in this layer).

- Layer 3: Every node in this layer is a circle node labeled N. The i-th node calculates the ratio of the i-th rule's firing strength to the sum of all rules' firing strengths, as in (7):

$$\overline{w}_j = \frac{w_j}{w_1 + w_2 + w_3 + w_4 + w_5} \tag{7}$$

For convenience, outputs of this layer will be called *normalized firing strengths*

- Layer 4: Every node i in this layer is a square node with a node function:

$$O_j^4 = \bar{w}_j f_j = \bar{w}_j \left( p_j x + q_j y + r_j \right) \quad (8)$$

Where $\bar{w}_j$ is the output of layer 3, and {pj, qj, rj} is the parameter set. Parameters in this layer will be referred to as consequent parameters.

$$\begin{cases} O_1^4 = \bar{w}_1 f_1 = \bar{w}_1 \left( p_1 x + q_1 y + r_1 \right) \\ O_2^4 = \bar{w}_2 f_2 = \bar{w}_2 \left( p_2 x + q_2 y + r_2 \right) \\ O_3^4 = \bar{w}_3 f_3 = \bar{w}_3 \left( p_3 x + q_3 y + r_3 \right) \\ O_4^4 = \bar{w}_4 f_4 = \bar{w}_4 \left( p_4 x + q_4 y + r_4 \right) \\ O_5^4 = \bar{w}_5 f_5 = \bar{w}_5 \left( p_5 x + q_5 y + r_5 \right) \end{cases} \quad (9)$$

- Layer 5 The single node in this layer is a circle node labeled E that computes the overall output as the summation of all incoming signals, i.e, as in (10):

$$O_1^5 = f = U_{\mathrm{ANFIS}} = \sum_{j=1}^{5} \bar{w}_j f_j \quad (10)$$

Where $x, y$ is the input: $x = \Delta\omega$ and $y = \Delta Pe$; Output signal is in layer 5 $f$ is the output, shown in Figure 4.

*Hybrid Learning Algorithm*

From the proposed ANFIS architecture in Figure 4, it is observed that given the values of premise parameters, the overall output can be expressed as a linear combinations of the consequent parameters. More precisely, the output f in Figure 4 can be rewritten as in (11).

$$\begin{aligned} f = {} & \frac{w_1}{w_1 + w_2 + w_3 + w_4 + w_5} f_1 \\ & + \frac{w_2}{w_1 + w_2 + w_3 + w_4 + w_5} f_2 \\ & + \frac{w_3}{w_1 + w_2 + w_3 + w_4 + w_5} f_3 \\ & + \frac{w_4}{w_1 + w_2 + w_3 + w_4 + w_5} f_4 \\ & + \frac{w_5}{w_1 + w_2 + w_3 + w_4 + w_5} f_5 \end{aligned} \quad (11)$$

# 4. Simulation Results

In this section the ANFIS system is simulated using Matlab-Simulink [12].

In power system analysis, the parameters are usually convenient to user a per unit system to normalize system variables. The simulation parameters are selected as following Table 1 in literature [14].

***Table 1.*** *Synchronous Machine Parameters*

| Symbol | Parameters | Value |
|---|---|---|
| $R_1$ | Stator winding resistance at $15^0$C | 0.0077 pu |
| $R_2$ | Rotor winding resistance at $15^0$C | 0.126 pu |
| $x_d$ | Direct axis synchronous reactance | 1.0494 pu |
| $x_q$ | Quadrature axis synchronous reactance | 0.648 pu |
| $x'_d$ | Direct axis transient reactance | 0.2887 pu |
| *x''d* | Direct axis over transient reactance | 0.191 pu |
| *xe* | Stator leakage reactance | 0.1244 pu |
| *xq* | Quadrature axis synchronous reactance | 0.648 pu |
| *x"q* | Quadrature axis over transient reactance | 0.197 pu |
| *T'do* | Excitation winding time constant when stator winding open circuit | 6.88 s |
| *Cosφ* | Rated power factor | 0.85 |
| *H* | The coefficient of inertia | 1.5 |
| *S* | Rated capacity | 1.0 pu |
| *P* | Rated power | 0.85 pu |
| *Q* | Rated power | 0.85 pu |
| *Ut* | Rated voltage | 1.0 pu |
| *It* | Rated current | 1.0 pu |
| *ω* | Rated angular speed of rotor | 1.0 |
| *f* | Rated frequency | 50 Hz |

(pu = Per unit, Hz = Hertz, s = second.)

- With PSS-2A and excitation system is shown in Figure 5.

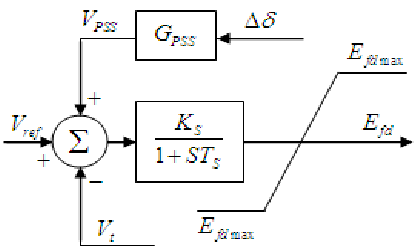


***Figure 5.*** *PSS-2A and excitation system*

The IEEE Type-ST1A dynamic equation [9] with PSS-2A is shown as in (12):

$$\dot{E}_{fd} = \frac{1}{T_A}\left[ K_A \left( V_{ref} + V_{PSS} - V_t \right) - E_{fd} \right] \quad (12)$$

- With ANFFIS and excitation system is shown in Figure 6.

The IEEE Type-ST1A dynamic equation with ANFIS is shown as in (13):

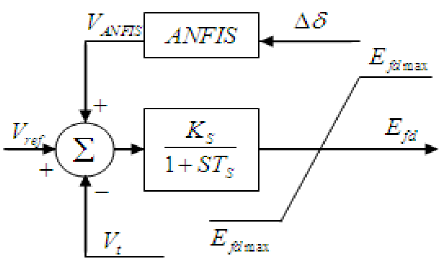


***Figure 6.*** *ANFIS and excitation system*

$$\dot{E}_{fd} = \frac{1}{T_A}\left[K_A\left(V_{ref} + V_{ANFIS} - V_t\right) - E_{fd}\right] \qquad (13)$$

*The simulation results:*

At the time t=0s, the generator is connected with the power system. We compare the performances of three different approaches: 1) the power systems using traditional AVR. 2) The power systems using PSS algorithm. 3) The power systems using ANFIS algorithm. Figure 7 and Figure 8 show simulation results of the characteristics of rotor speed. Figure 8 gives rotor speed using ANFIS algorithm has fluctuated in 2.2 seconds (from 0s to 2.2s) and stable with ω=1pu.

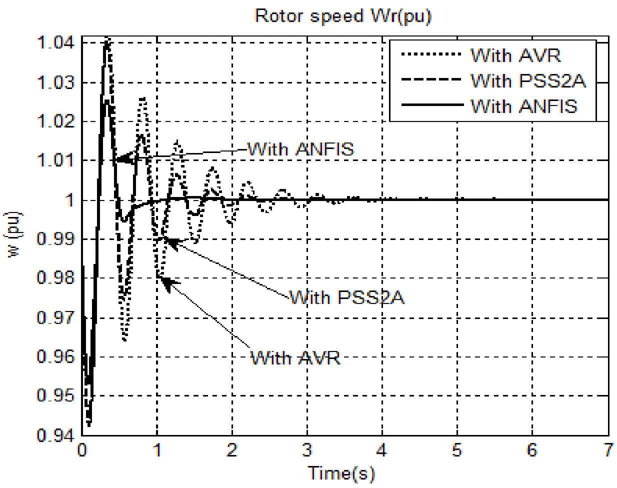


***Figure 7.*** *The characteristic of angular speed of rotor, the generator is connected into the power system at time t=0s*

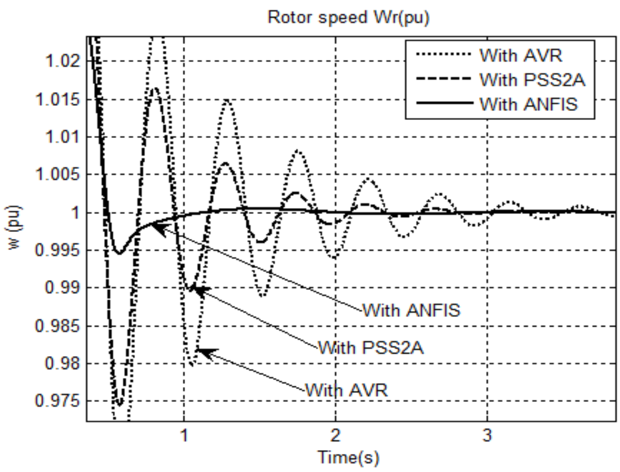


***Figure 8.*** *The characteristic of angular speed of rotor zoom in Figure 7*

Figure 8 also gives power systems using ANFIS algorithm works better than AVR and PSS algorithm.

At time t = 8s, we add connected load 300MV to power system. Figure 9 show that simulation results of the characteristics of rotor speed under three different methods. Figure 9 show that the rotor speed has fluctuated in 2.23 seconds (from 8s to 10.23s) and stable with ω=1pu. Figure 9 also show that the performance of the power system using ANFIS algorithm is superior to another two methods.

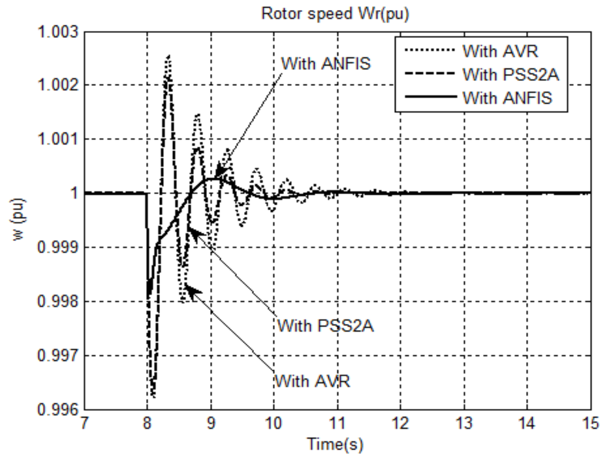


***Figure 9.*** *The characteristic of angular speed of rotor, the load power of 300MW is connected into the power system after time 8s*

Figure 10, Figure 11 and Figure 12 give the simulation results of the characteristic of available power under three different methods.

Figure 11 shows power of the power system using ANFIS algorithm has fluctuated in 2.3 seconds (from 0s to2.3s) and stable with Pe=0.85pu at time t = 0s the generator is connected to power system.

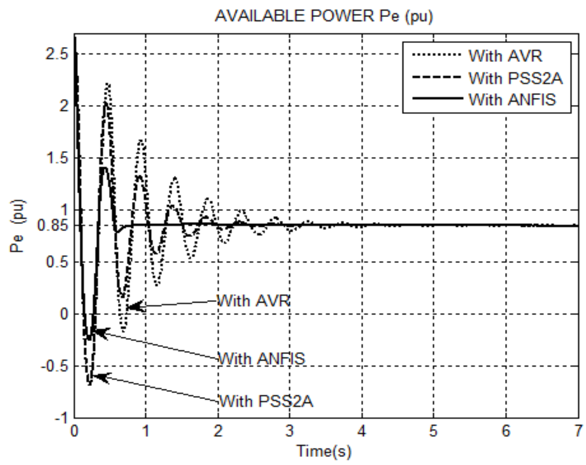


***Figure 10.*** *The characteristic of angular speed of power, the generator is connected into the power system at time t=0*

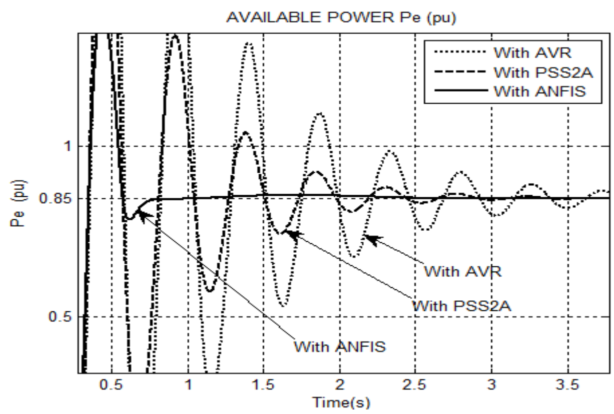


***Figure 11.*** *The characteristic of angular speed of power, the generator is connected into the power system zoom in Figure 10*

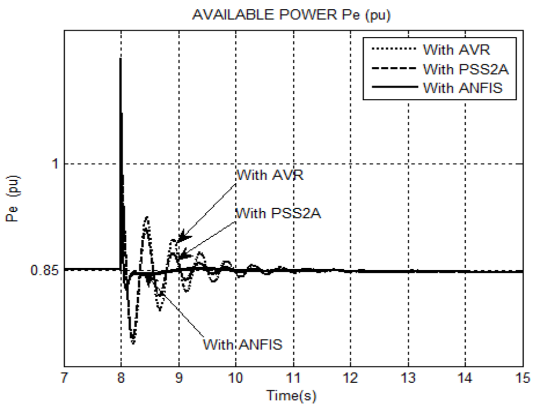


***Figure 12.*** *The characteristic of angular speed of power, the load power of 300MW is connected into the power system after time 8s*

After 8 seconds, we connect a load of 300MW into the power system. Figure 12 illustrates power of the power system using ANFIS algorithm has fluctuated in 2.23 seconds (from 8s to 10.23s) and stable with Pe=0.85pu.

Through the results in Figure 10, Figure 11, Figure 12, we see that the power system stability using ANFIS algorithm can achieve better results than AVR and PSS methods.

# 5. Conclusion

In this paper, an ANFIS algorithm has been presented for stability control of the power system. The main contributions of the paper are that we use ANFIS algorithm for the problem of small signal stability in power system which enhancing damping of system oscillations via generator excitation control. This study provides an alternative algorithm for power system stabilizer PSS to reduce the response time of the rotor speed, the response time of output power of the generator and reinforcing the power stability in the power system. Simulation results show that the ANFIS algorithm can achieve better results than PSS and AVR methods.

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