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TURBINE DYNAMICS STUDY CONTROL USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

A. Rezaeifar [1] R. Effatnejad [2,*] A. Dehghani Tafti [2]

1. Electrical Engineering Department, Science and Research Branch, Islamic Azad University, Karaj, Iran
a.rezaeifar@yahoo.com
2. Electrical Engineering Department, Karaj Branch, Islamic Azad University, Karaj, Iran
reza.efatnejad@kiau.ac.ir, dehghani@kiau.ac.ir
**. Corresponding author*

Abstract- This paper presents an application of Adaptive Neuro-Fuzzy Inference System (ANFIS). The control structure of the purposed consists fuzzy logic to damp the low frequency oscillations of power system and neuro identifier to track the dynamic behavior of the plant. In practical for damping of disturbance in the power system, Automatic Voltage Controller (AVR) is used. To develop this controller adding a supplementary signal called Power System Stabilizer (PSS) is recommend. However, there are some problems like complexity limitations like as borderlines, high number of parameters. Because of the mentioned limitations the performance of the controllers reduces. The neuro-fuzzy is a nonlinearity method for analyze without any complexity. In this paper, we will demonstrate neuro-fuzzy method application considering the results of the classic PSS, in high accuracy and low complexity.

Keywords: ANFIS, AVR Controller, PSS, Neuro-Fuzzy.

I. INTRODUCTION

During a fault in practical power system, turbines dynamic's stability may deteriorate [1]. Automatic voltage regulator (AVR) [1-3] is the simplest controller that use for damping of disturbance. To develop the performance of AVR using a supplementary controller called Power System Stabilizer (PSS) [1-3] is recommended. The PSS is able to damp the electromechanical oscillation of the generator in power system. Linear equations in designing of PSS make problems that they directly effect in quantity of controller performance in use in power system.

The intelligent methods like neuro-fuzzy approaches are introduced in literature [4, 5]. The neuro-fuzzy methods have training procedures and testing steps. By loading data for training controller, suitable response for control system can be generated. In this paper the classical PSS algorithm is used for training process. In this procedure, all the generated data in classical PSS load will be trained in fuzzy logic controller. At the first step, the turbine dynamic model is demonstrate. So considering AVR and PSS, the ultimate part of our studying is applicable of the neuro-fuzzy.

II. AVR CONTROLLER

In this paper, we use Hefron-Philips model for studying of turbine dynamics. This is three-degree model of synchronous machine [1]. In this model, the ohmic and induction's drop in front of inductions flux ($\omega\varphi_d$, $\omega\varphi_q$) and effect of dampers will be ignored. Considering $dq0$ transferring and the three-phase (a, b, c) of stator and rotor is changed to $dq0$ axis and three variable parameters x, state vector will be:

$$X = \begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix}^T \tag{1}$$

Equations for Hefron-Philips model will be:

$$x_1' = \omega_0 x_2 \tag{2}$$

$$x_2' = \frac{1}{J}U_1 - \frac{1}{J}T_e - \frac{D}{J}x_2 \tag{3}$$

$$x_3' = \frac{1}{T_{do}'}[U_2 - x_3 + (x_d - x_d')i_d] \tag{4}$$

where, $U_1 = T_m$ is turbine mechanical torque, $U_2 = E_{FD}$ is exciter field voltage. After linearizing above equations:

$$\Delta x_1' = \Delta\omega_0 x_2 \tag{5}$$

$$\Delta x_2' = \frac{1}{J}\Delta U_1 - \frac{1}{J}\Delta T_e - \frac{D}{J}\Delta x_2 \tag{6}$$

$$\Delta x_3' = \frac{1}{T_{do}'}\left[\Delta U_2 - \Delta x_3 + \left(x_d - x_d'\right)\Delta i_d\right] \tag{7}$$

where, i_d and T_e have to clear in according to other parameters. At the first Δi_d is:

$$i_d = \left(\frac{1}{x_d'}\right)x_3 - \left(\frac{V_B}{\dot{x}_d}\right)\cos x_1 \tag{8}$$

$$\Delta i_d = \left(\frac{1}{x_d'}\right)\Delta x_3 + \left(\frac{V_B \sin x_{10}}{x_d'}\right) \tag{9}$$

$$\Delta x_1 = Y_d \Delta x_3 + F_d \Delta x_1 \tag{10}$$

$$i_q = \frac{V_B \sin x_1}{x_q} \tag{11}$$

$$\Delta i_q = \frac{V_B \cos x_{10}}{x_q} \tag{12}$$

$$\Delta x_1 = F_q \Delta x_1 \quad (13)$$

where, x_{10} is power angle in operating point as ω_0.

$$y_d = \frac{1}{x'_d} \quad (14)$$

$$F_d = \frac{V_B \sin x_{10}}{x'_d} \quad (15)$$

$$F_q = \frac{V_B \cos x_{10}}{x_q} \quad (16)$$

$$T_e = c_3 x_3 \sin x_1 + c_4 \sin 2x_1 \quad (17)$$

After linearizing, we get:

$$\Delta T_e = c_3 \sin x_{10} \Delta x_3 + \left[c_3 x_{30} \cos x_{10} + 2c_4 \cos 2x_{10} \right] \Delta x_1 \quad (18)$$

$$K_1 = \left(\frac{V_B^2 x_{30} \cos x_{10}}{x'_d} \right) + V_B^2 \left[\frac{1}{x_q} - \frac{1}{\dot{x}_d} \right] \cos 2x_{10} \quad (19)$$

$$K_2 = \frac{V_B^2 \sin x_{10}}{x'_d} \quad (20)$$

$$K_3 = \left(\frac{1}{1 + \left(x_d - x'_d \right) y_d} \right) \quad (21)$$

$$K_4 = \left(x_d - x'_d \right) F_d \quad (22)$$

With above mentioned equations will have:

$$\Delta x'_1 = \omega_0 \Delta x_2 \quad (23)$$

$$\Delta x'_2 = \frac{1}{J} \Delta U_1 - \frac{K_1}{J} \Delta x_1 - \frac{D}{J} \Delta x_2 - \frac{K_2}{J} \Delta x_3 \quad (24)$$

$$\Delta x'_3 = \left(\frac{1}{K_3 T'_{do}} \right) \left[K_3 \Delta U_2 - \Delta x_3 + K_4 \Delta x_1 \right] \quad (25)$$

State space will be:

$$\begin{bmatrix} \Delta x_1 \\ \Delta x_2 \\ \Delta x_3 \end{bmatrix} = \left[\begin{bmatrix} 0 & 0 & 0 \\ \frac{-x_1}{J} & \frac{-D}{J} & 0 \\ \frac{K_4}{K_3 T'_{do}} & 0 & \frac{-1}{K_3 T'_{do}} \end{bmatrix} \right] + \begin{bmatrix} 0 & 0 \\ \frac{1}{J} & 0 \\ 0 & \frac{1}{T'_{do}} \end{bmatrix} \begin{bmatrix} \Delta U_1 \\ \Delta U_2 \end{bmatrix} \quad (26)$$

After using the Laplace transfer equations it will be as:

$$\Delta x_1(s) = \frac{\omega_0}{s} \Delta x_2(s) \quad (27)$$

$$\Delta x_2(s) = \left(\frac{1}{Js + D} \right) \left[\Delta U_1(s) - K_1 \Delta x_1(s) - K_2 \Delta x_3(s) \right] \quad (28)$$

$$\Delta x_3(s) = \left(\frac{K_3}{1 + sK_3 T'_{do}} \right) \left[\Delta U_3(s) - K_4 \Delta x_1(s) \right] \quad (29)$$

Block diagram of AVR system is shown in Figure 1. The Hefron-Philips model has shown in Figure 2.

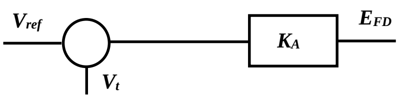

Figure 1. Block diagram of AVR, K_A is loop gain, *EFD* is output voltage of that forward to excitation field

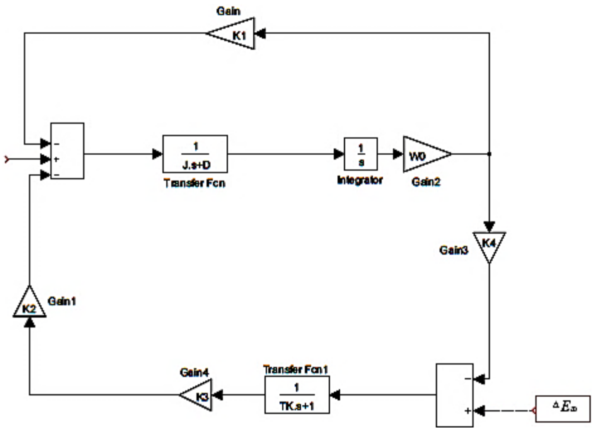

Figure 2. Dynamic structure of the Hefron-Philips model

With identifying ΔV_t in according with state parameters:

$$V_t = \sqrt{V_d^2 + V_q^2} \Rightarrow V_t^2 = V_d^2 + V_q^2 \Rightarrow$$

$$2V_{to} \Delta V_t = 2V_{do} \Delta Vd + 2V_{qo} \Delta V_q \Rightarrow \quad (30)$$

$$\Delta V_t = \frac{V_{do}}{V_{to}} \Delta V_d + \frac{V_{qo}}{V_{to}} \Delta V_q$$

The simplest case of generator connection to infinite net is directly:

$$V_d = V_B \sin x_1 \Rightarrow \Delta V_d = V_B \cos x_{10} \Delta x_1 \quad (31)$$

$$V_q = V_B \cos x_1 \Rightarrow \Delta V_q = -V_B \sin x_{10} \Delta x_1 \quad (32)$$

With above equation, we will have:

$$\Delta V_t = \left(V_B \frac{V_{do}}{V_{to}} \cos x10 - V_B \frac{V_{qo}}{V_{to}} \sin x_{10} \right) \Delta x = K_5 \Delta x_1 \quad (33)$$

$$\begin{cases} V_d = V_B \sin x_1 - x_e i_q \\ V_q = V_B \cos x_1 + x_e i_d \end{cases} \quad (34)$$

$$\begin{cases} \Delta V_d = V_B \cos x_{10} \Delta x_1 - x_e \Delta i_q \\ \Delta V_q = V_B \sin x_{10} \Delta x_1 + x_e \Delta i_d \end{cases} \quad (35)$$

$$\Delta V_t = \left[-\frac{V_{do}}{V_{to}} F_q x_e + \frac{V_{qo}}{V_{to}} F_d x_e \right] \Delta x_1 + \left[\frac{V_{qo}}{V_{to}} y_d \right] \Delta x_3 \quad (36)$$

$$K_5 = -\frac{V_{do}}{V_{to}} F_q x_q + \frac{V_{qo}}{V_{to}} F_d \dot{x}_e \quad (37)$$

$$K_6 = \frac{V_{qo}}{V_{to}} y_d \quad (38)$$

$$\Delta V_t = K_5 \Delta x_1 + K_6 \Delta x_3 \quad (39)$$

The AVR and Hefron- Philips model is shown in Figure 3. This model includes voltage transducer and AVR exciter blocks. The values of parameters and operating condition used for simulation of system are given in Table 1.

III. PSS CONTROLLER

For compensation of limitation in AVR loops control, supplementary loop control called power system stabilizer (PSS) is included to AVR controller and turbine model and the PSS develops gain performance. This stabilizer is a controller that, and error signal $\Delta\omega_S$ generates additional control signal for AVR that results LFO signals stability.

The basic function of a PSS is adding the damping to the generator rotor oscillations by controlling its excitation using auxiliary stabilizing signal. To provide damping, the stabilizer must produce a component of electrical torque in phase with the rotor speed deviations.

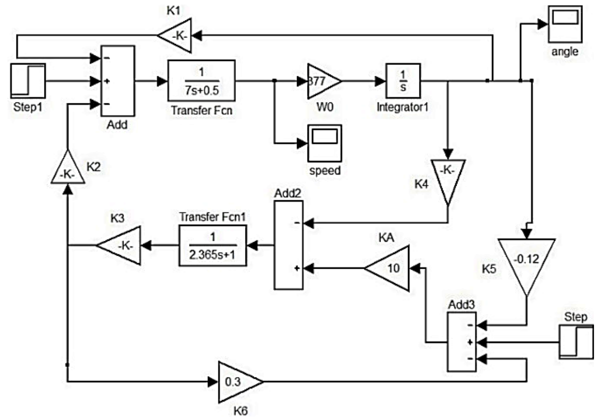

Figure 3. Turbine dynamics model with AVR

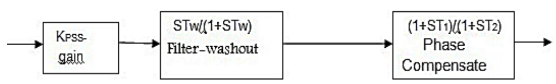

Figure 4. PSS block diagram

A PSS consists three components as Phase Compensate, Washout (Filter), and Gain. The gain determines the amount of damping introduced by PSS. Ideally, gain should be set at a value corresponding to maximum damping. Signal washout block serves as a high-pass filter with the time constant T_w high enough to allow signals associated with oscillations in ω_r to pass unchanged. Without it, steady changes in speed would modify the terminal voltage. It allows the PSS to respond only to changes in speed. The phase compensation block provides the appropriate phase-lead characteristic to compensate for the phase lag between the exciter input and the generator electrical torque.

The Figure 4 shows a single first-order block. In practice, two or more first-order blocks may be used to achieve the desired phase compensation. In some cases, second-order blocks with complex roots have been used. The location of the PSS signals is important. That is out of our decision [1-3]. We suppose that location is in the best situation.

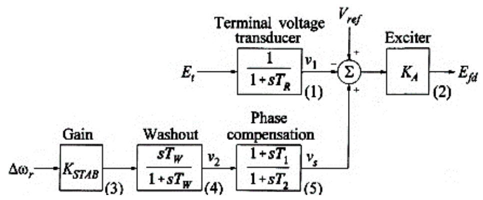

Figure 5. Power system stabilizer, thyristor excitation system of PSS model [1]

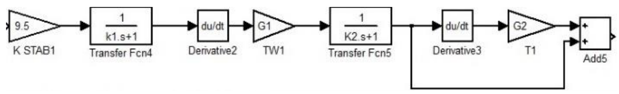

Figure 6. The PSS dynamic mode

The theoretical basic for PSS has been illustrated with the aid of the block diagram which is shown in Figure 6. This is an extension of block diagram of Figure 3. Since the purpose of a PSS is to introduce a damping torque component, a logical signal to use for controlling generator excitation will be the speed deviation $\Delta\omega$. If the exciter transfer function $G_{ex}(S)$ and the generator transfer function between ΔE_{jd} and ΔT_e were pure gains, a direct feedback of $\Delta\omega$ would result in a damping torque component.

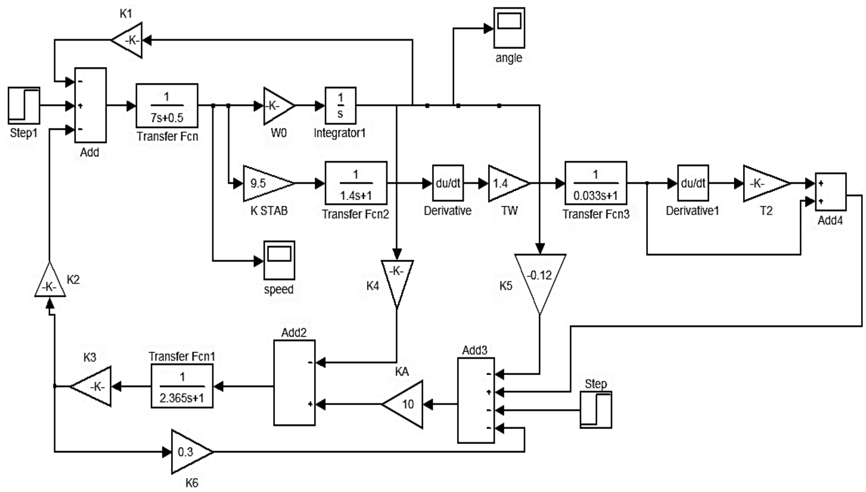

Figure 7. Turbine model with AVR and PSS

However, in practice both the generator and exciter (depending on its type) exhibit frequency dependent gain and phase characteristics. Therefore, the PSS transfer function, $G_{PSS}(S)$, should have appropriate phase compensation circuits to compensate for the phase lag between the exciter input and electrical torque.

In the ideal case, with the phase characteristics of $G_{PSS}(S)$ being an exact inverse of exciter and generator phase characteristics to be compensated, the PSS would result in a pure in damping torque at all oscillating frequencies. System's parameters are given in Table 1 in the Appendix.

IV. NEURO-FUZZY CONTROLLER

The dynamic models of turbine and AVR are designed with mathematical equations and Laplace transfer up to now which describe classical method of PSS design (Figure 7). In this part a new algorithm will be described instead of PSS in dynamic models. This algorithm combines two logics as, Fuzzy Logic (FL) and Artificial Neural Network (ANN). A Fuzzy Logic Controller (FLC) provides a possible alternative to capture the qualitative schematic of human reasoning and making decide process to control a system. The ANN is used for learning and adaptation.

To take advantage of ability of them, two paradigms are combined and used to design an adaptive neuro-fuzzy PSS. Structure of the control consists of an Adaptive Neuro-Identifier (ANNI) and an adaptive Neuro-Fuzzy Controller (NFC). ANNI is for track the dynamic characteristic of the plant and NFC is for damping of the oscillations of the power system. We have to introduce link weights between Input Scaling Factors (ISFs) and the input layer of fuzzy controller in mamdani-type and sugeno type. In this case, we could have maneuver on Input Membership Factors (IMFs) and Consequent Parameters (CPs) [6, 7].

Modification of the various parameters like as scaling factors, membership function (Figure 8), and rules increase/reduce the performance of the FLSs. More engineers emphasis on the parameters optimization of them [8] and have little attention on scaling factors. By modification on SFs, the working range will change and its changing has effect on the output gain and directly modifies MFs and controller rules. The SFs play a very important role in high quality design of controller.

ANFIS is the implementation of Fuzzy Inference System (FIS) to adaptive networks for developing fuzzy rules with suitable membership functions to have required inputs and outputs. The FIS is a popular and cardinal computing tool to watch fuzzy If-Then rules and reasoning compose. An adaptive network is a feed forward multilayer ANN with partially or completely, adaptive nodes in which the outputs are predicated on the parameters of the adaptive nodes and the adjustment of parameters due to error term is specified by the learning rules [4, 5].

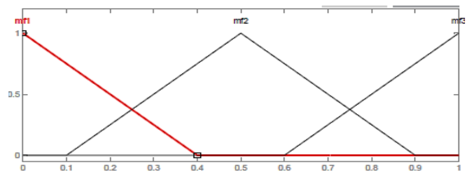

Figure 8. Membership function

The ANFIS is a multilayer feed-forward network, which uses neural network learning algorithms and fuzzy reasoning to map inputs into an output. Indeed, it is a Fuzzy Inference System (FIS) implemented in framework of adaptive neural networks in Anfinsen following steps:
Step 1- Experimental work
Step 2- Expert ANFIS system
Step 3- Membership function for expert ANFIS
Step 4- Transfer data for surface roughness level
Step 5- Development and analyzing fuzzy system

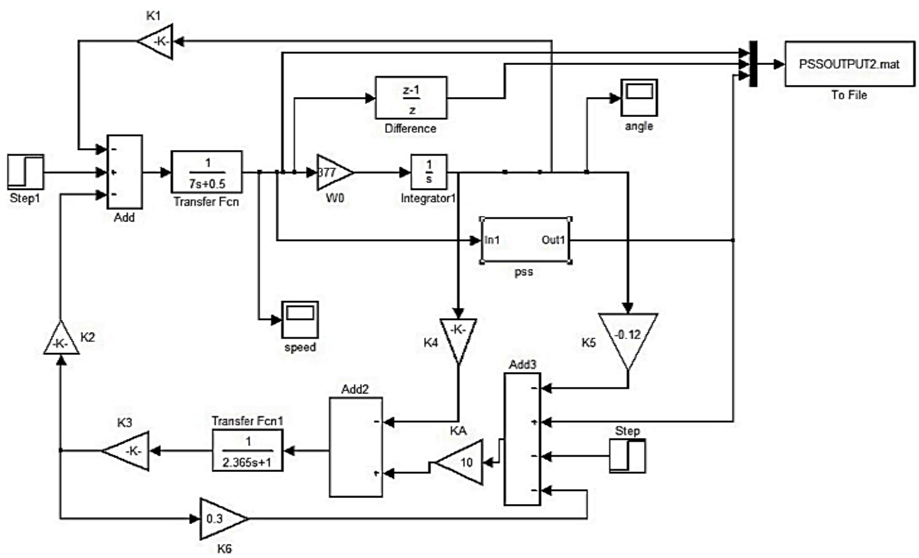

Figure 9. Parallel PSS with neuro-fuzzy for training

With above mentioned details, this controller is organized with two components. A fuzzy part is the heart of work, expressing many influence parameters in control surface. Tuning membership functions, rules operations and scaling factors make optimal regulation. So, this express with many methods and technique are using for adjusting parameters. In this component, we train data and update them. In present paper, the parallel conventional PSS with neuro-fuzzy are used and trained with ANFIS and updated with them (Figure 9). The second component is neuron. Which is in inside of the software. The procedure will be:

- Training and Load Data: For training (Figure 6), the parallel classical PSS method with fuzzy is used. In this step, all requirement data provided from classical PSS will be loaded in ANFIS. This step is shown in Figure 10.

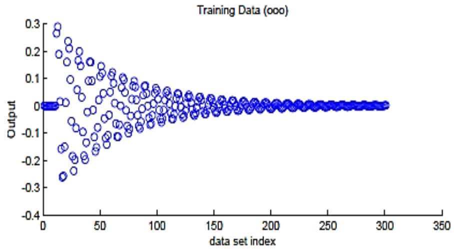

Figure 10. Load and training data

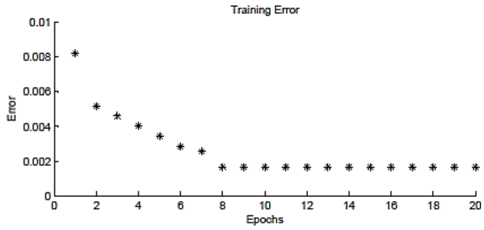

Figure 11. ANFIS editor for training FIS

- Grid Partition: In this step, we should select a kind of grid for generating FIS. The applicable grid in this paper is Gaussian (gaussmf).
- Training FIS: Error tolerance and epochs are two items in this step. As shown in Figure 11 epoch's equal 20. Finally the model will be as Figure 14.

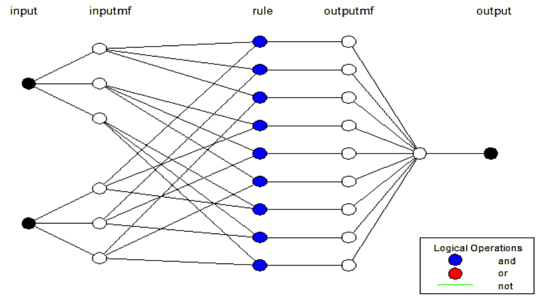

Figure 12. Structure of ANFIS for two input and one output

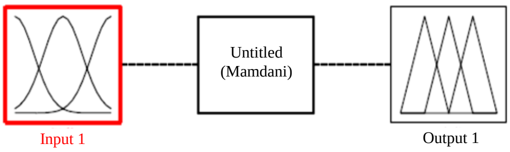

Figure 13. Relation between input-output in FIS editor

V. SIMULATION RESULTS

Results of AVR controller applying in turbine are shown in this part. The angle output with AVR controller is shown in Figure 15 which the AVR tries to damp fault but that's reaction is slow. Figure 16 shows the results similar that for speed. In both of them time is more than 30 second. To compensate this delay the PSS is used. The supplementary signals applying is very clear for damping of the fault.

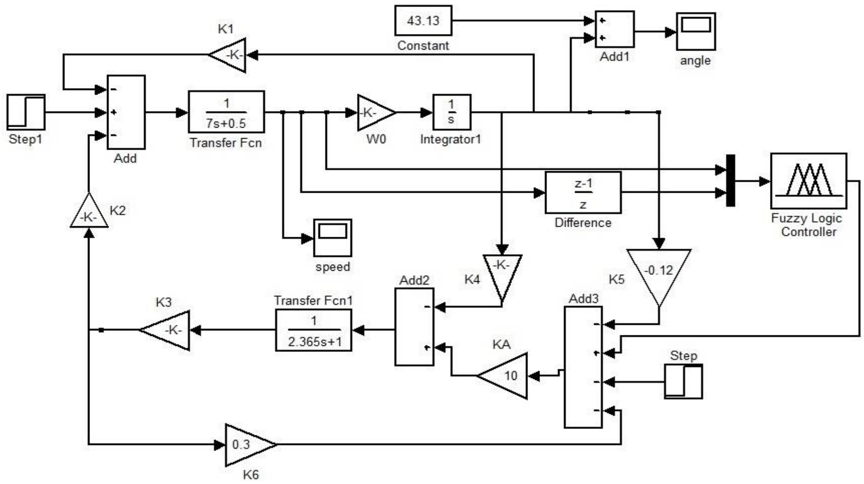

Figure 14. Turbine with AVR and ANFIS

The output domain and reaction time are shown in Figure 17 and Figure 18 which are comparable better than the previous ones. With adding constant parameters for bias and verifying the parameters, the convergence value are obtained. The ANFIS is used in applied PSS is shown in Figure 19. Regarding to the software setting, the time scale is 10 times bigger than of the figures scale. Figure 20 shows ANFIS without any complexity in the same results. In this study, three types of turbine controller are introduced.

As shown in Figure 15 and Figure 16, the AVR controller tries to damp the fault and stabilize the system. But in practical state, the response time is very week. In fact, the AVR controller cannot control a power system fault. For enhancement of responsibility time, a supplementary signal called PSS is added to the controller. The results are shown in Figures 17 and 18.

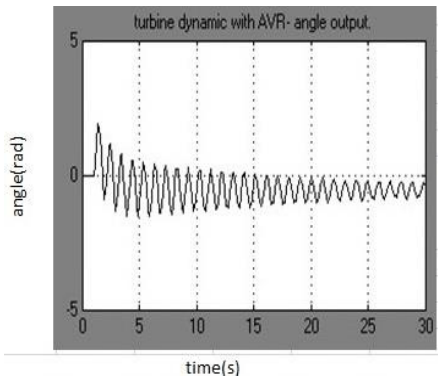

Figure 15. Turbine with AVR-angle output

The response time in these figures show, good performance of the controller in comparing with the first step. In third steps, we use ANFIS for optimizing of PSS. The results of domain and response time of the optimizer has been compared with the second step in Figure 19.

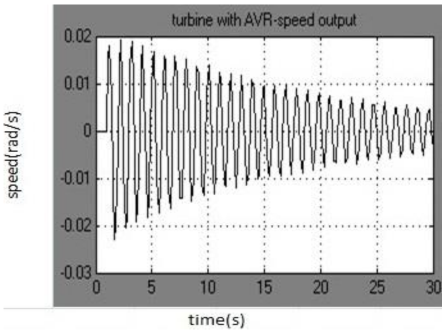

Figure 16. Turbine with AVR-speed output

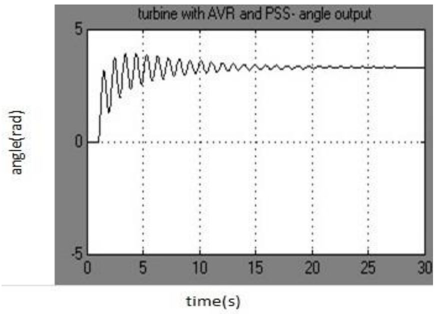

Figure 17. Turbine with AVR and PSS-angle output

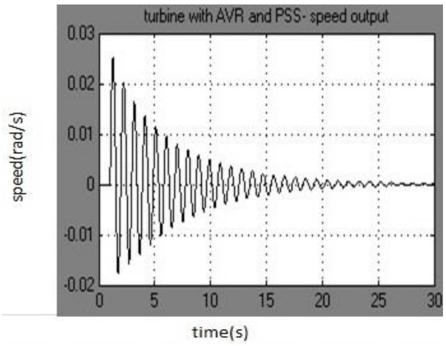

Figure 18. Turbine with AVR and PSS-speed output

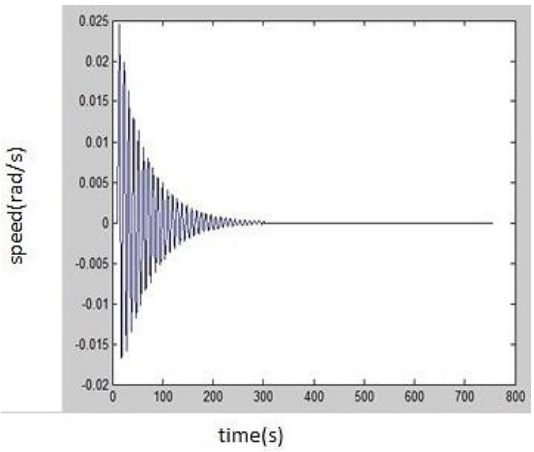

Figure 19. Turbine with AVR and ANFIS-speed output

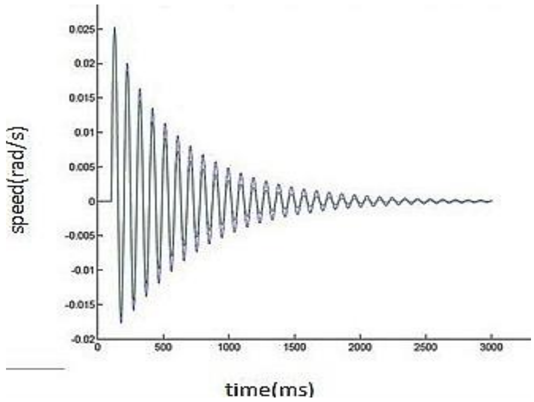

Figure 20. Comparison between ANFIS (Green) and PSS (Blue) for speed

VI. CONCLUSIONS

An adaptive neuro-fuzzy PSS is presented in this paper. The proposed stabilizer is made to be adapted by the online modification according to the procedure. The frequency response time in AVR is not satisfied. For compensate that, adding PSS is effective and after fault, system can be stable immediately. However, in ANFIS controller, after training, the response time and amplitude will be ameliorate in compare with PSS. Therefore, our reasons for recommending to use the ANFIS will be:
- That is nonlinear
- That does not need complex equations
- That does not need to limitation
- That has high accuracy
- Good performance
- Suitable response time for system stabilizing

APPENDIX

Coefficients

Parameters	Figure 1	Figure 2
$K_1=K$	0.7643	-
K_1	43.13	-
A	7	1.4
B	0.5	1
$W_0=K$	377	-
K_4	1.4187	-
K_5	-0.12	-
K_A	10	-
K_6	0.3	-
K_3	0.3230	-
C	2.365	0.0335
D	1	1
T_w	-	1.4
T_2	-	0.154
K_{Stab}	-	9.5

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BIOGRAPHIES

Abdolreza Rezaeifar was born in Iran, 1974. He received the B.Sc. degree in the field of Electronic Engineering from Shahid Beheshti University, Tehran, Iran, in 1998. Then, he worked in the Oil and Gas Industrial Companies in the field of Instrumentation and Control System (I&C). He is studying as the M.Sc. student at the Science and Research Branch, Islamic Azad University, Alborz, Iran from 2011. He moved to power plant industrial from 2007 up to now. He also worked in Process and I&C Department and worked with kind of turbines. His fields of research areas include to turbine dynamic, and Instrumentation and Control System.

Reza Effatnejad Reza Effatnejad was born in Abadan, Iran on December 14, 1969. He is a Ph.D. in Electrical Engineering and an Assistant Professor in Karaj Branch, Islamic Azad University, Karaj, Iran. He has published more than 42 published papers in journals and international conferences, and three books in the fields of energy management, energy efficiency, energy conservation in industry and building sectors, combined heat and power (CHP) and renewable energy. His fields of research areas include to labeling in home appliances and energy auditing in industry.

Abdolreza Dehghani Tafti was born in Karaj, Iran, on December 6, 1976. He received his B.Sc. degree in Electronic Engineering from Karaj Branch, Islamic Azad University, in 1999, and the M.Sc. degree in Control Engineering from South Tehran Branch, Islamic Azad University, Tehran, Iran in 2001. He received his Ph.D. in Control Engineering from Science and Research Branch, Islamic Azad University, Tehran, Iran in 2010. His fields of research areas include pattern recognition, estimation, and neuro-fuzzy networks.