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Performance Evaluation of an ANFIS Based Power System Stabilizer Applied in Multi-Machine Power Systems

A. A GHARAVEISI [1,2] A.DARABI[3] M. MONADI[4] A. KHAJEH-ZADEH[5] M. RASHIDI-NEJAD[1,2,5]
1. Shahid Bahonar University of Kerman, Kerman, Iran
2. International Research for Science & High Technology, Mahan, Iran
3. Shahrood University of Technology, Shahrood,Iran
4. Electric Distribution Company Ahvaz, Iran
5. Design and Engineering Department of North Electric Distribution Company Kerman, Iran
22 Bahman Boulvard, Elec. Eng. Dept. Kerman
IRAN

Abstract: - Power system stabilizers (PSSs) are utilized in order to make power systems stable after a large or small disturbance. Therefore PSSs must be capable of providing appropriate stabilization signal over a broad range of operational conditions and disturbances. Due to the fact that PSSs are widely used in power industry, any appropriate improvements in controlling methods of PSSs are important as well. Recently, Fuzzy logic is used as a robust control design method and FPSS is proved to have a good answer for generating appropriate control signal. However fuzzy logic controllers (FLCs) are based on empirical contract rules, however there is no systematic method known for designing of a FLC. A self learning adaptive network based fuzzy inference system (ANFIS) type power system stabilizer (ANFPSS) is presented in this paper.
In this approach, the fuzzy rules and membership functions of the fuzzy PSS is tuned automatically by the learning algorithm. The proposed technique is illustrated on a 9-bus, 3-machine power system. Results show that ANFPSS has a satisfactory performance under various and different conditions of power systems and related faults.

Key-Words: - Multi-Machine Power System, Adaptive Networks Based Fuzzy Inference System (ANFIS)

1 Introduction

Power systems are usually large non-linear systems, which are often subjected to low frequency electromechanical oscillations. Power System Stabilizers (PSSs) are often used as an effective and economic means for damping the generators' electromechanical oscillations and enhance the overall stability of power systems. Power system stabilizers have been applied for several decades in utilities and they can extend power transfer stability limits by adding modulation signal through excitation control system. They provide good damping; thereby contribute in stability enhancement of the power systems.
Designing PSS is an important issue from the viewpoint of power system stability. Conventional PSSs (referred to as CPSS) use transfer functions designed for linear models representing the generators at a certain operating point [1,2]. However, as they work around a particular operating point of the system for which these transfer functions are obtained, they are not able to provide satisfactory results over wider ranges of operating conditions. In other words, according to the fact that the gains of the mentioned controller are determined only for a particular operating condition, they may not yet be valid for a wide range around or for other new conditions [3].
This problem is overcome by using Fuzzy logic based technique for designing of PSSs. Fuzzy logic systems (FLCs) allows us to design a controller using linguistic rules without knowing the exact mathematical model of the plant[4,5]. The application of Fuzzy Power System Stabilizers (FPSSs) has been motivated because of some reasons such as improved robustness over that obtained using conventional linear control algorithm, simplified control design for difficult-to-be-modeled systems and simplified implementation[3,6]. FLCs are very useful in the case a good mathematical model for the plant is not available; however, experienced human operators are available for providing qualitative rules to control the system. In some paper to improve the performance of FPSSs a hybrid FPSS is presented. In [7] a FLC is used with two CPSS, also Hybrid PSSs using fuzzy logic and/or neural networks or Genetic Algorithms (GA) have been reported in

some literature [8,9].

However, there is no systematic procedure for designing FLCs. The most common approach is to define Membership Functions (MFs) and IF-THEN rules subjectively by studying an operating system or an existing controller. So, an adaptive network based approach presented in [10] to choose the parameters of fuzzy system using a training process. In this technique an adaptive network is used to find the best parameter of fuzzy system.

In this paper, an adaptive neuro fuzzy inference system (ANFIS) based PSS is developed, which uses the speed, and its deviation as the inputs. The ANFPSS uses a zero order Sugeno-type fuzzy logic controller whose membership functions and consequences are tuned by back-propagation method. Fuzzy rules and MFs of the controller can be tuned automatically by learning algorithm.

The proposed technique is illustrated on a 9-bus, 3-machine power system. MATLAB/SIMULINK and fuzzy logic toolbox have been used for system simulation. The results demonstrate that the proposed self-learning ANFPSS provides a good damping over a wide range of operation conditions and improves the stability margin of the system as well.

2. Adaptive Network Based Fuzz Inference System

In this article, an Adaptive-Network based fuzzy structure is employed to design a fuzzy logic power system stabilizer (FPSS). The FPSS considered, have two inputs that are components of the speed and its deviation. In this method, input parameters change to linguistic variable and suitable Membership Functions (MFs) should be chosen for them. Moreover, the rule base contains the fuzzy if-then rules of Takagi and Sugeno type, in which the output of each rule is a linear combination of input variables added by a constant term [10].

I. Structure of ANFIS

In this part, the structure of ANFIS for tuning parameter of a fuzzy inference system with two inputs and one output is explained. The structure of ANFIS which is shown in fig (1) consists of five layers [10]:

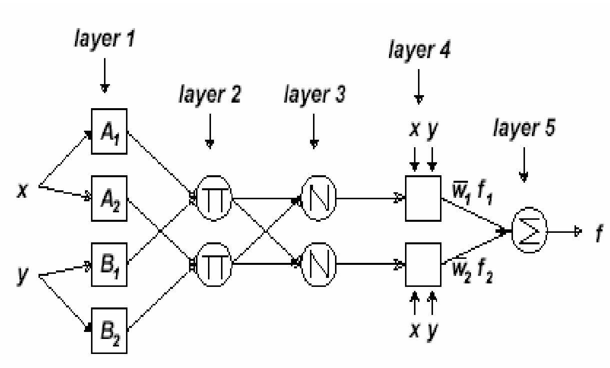

Fig.1 The structure of ANFIS with two inputs

Layer1:

Each node in this layer is an adaptive node with a node function shown in the following equation (1), and performs a membership function (MF):

$$O_i = \mu_{A_i}(x) \quad (1)$$

, where O_i is membership function of $\mu_{A_i}(x)$ and A is the linguistic label associated with this node. In this layer parameter of each MF are adjusted. In this work, MFs of these nodes are bell-shaped function.

Layer 2:

In this layer the output of each node represents the firing strength of each rule. Hence, the nodes perform the fuzzy AND operation, that its output is multiple of inputs as shown in equation (2):

$$W_i = \mu_{A_i}(x) * \mu_{B_i}(y), \qquad i = 1, 2, 3, \ldots \quad (2)$$

Layer 3:

As shown in equation (3), the nodes of this layer determine the normalized firing strength of each rule:

$$\bar{\omega}_i = \frac{\omega_i}{\sum_{i=1}^{n} \omega_i} \quad (3)$$

Layer4:

Each node in this layer is an adaptive node and in this layer parameters of output are adjusted. This output usually is a linear function of input.

Layer 5:

This layer has only one node and calculates the overall output as a summation of all input signals:

$$f = \sum_{i=1}^{n} f_i \quad (4)$$

Hence, an adaptive Network has been constructed, which is functionally equivalent to a fuzzy logic fault locator. This structure can update the MFs and rule base parameters.

3. ANFIS Based PSS

The ANFPSS is initially trained off-line. For this, typically disturbances under various operation conditions were applied to simulated Multi-Machine Power System. The main effective characteristic and condition of the power system by which the PSS operations could be distorted are assumed to be one of the fault positions, level of system load, and clearing time of protection devices. In other words a useful PSS should be able to generate proper, so an effective PSS must be able to generate suitable damping signals under various position of fault and different levels of load. Furthermore, if the protection system has not a proper operation and failed to clear fault in the shortest time, the backup protection would be activated after a determined time delay, so the PSS should be enable to send proper damping signal under this conditions.

For this, further to normal operation of power system, we simulated other critical conditions and used the obtained data in training process of ANFPSS, therefore the proposed PSS is able to damp oscillations under normal condition of power system and also conditions described bellow:

A. Various position of fault on power system: the ANFPSS can damp oscillation due to fault on different bus or along each line of power system.
B. Fault clearing time: the ANFPSS has good performance even if the main protection system failed and fault clearing time increases until backup protection operates with a determined time delay.
C. Level of load: the proposed ANFPSS has a nice operation when power system faces with a maximum %20 overload.

Initial parameters of MFs and IF-THEN rules are selected in a random manner and after training process the obtained MFs and rules are applied to power system as an ANFPSS.

3.1 ANFPSS Scheme

Figure (2). Shows the scheme of proposed ANFPSS and its application in a Multi-Machine power system.

A zero order Sugeno fuzzy controller with 18 rules is used for ANFPSS. The controller rules are of the form:

IF $\Delta\omega$ is Ai and P is Bi then u=Ki

Where Ai and Bi are fuzzy sets and Ki is a constant value.

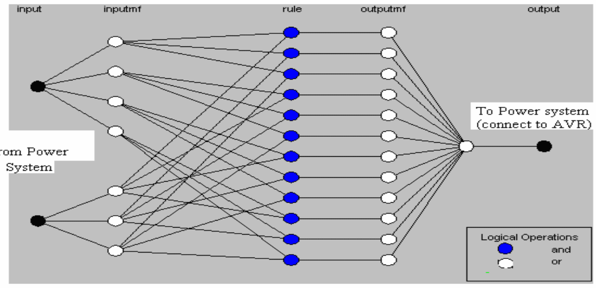

Fig.2 Proposed ANFPSS for Multi-Machine Power System

The MFs of two inputs of controller represent the triangle membership functions for each linguistic set and each input. These MFs, after training process, are shown in fig (3).

4. Simulation Result

The 3-Machine 9-Bus power system, shown in fig (4), is used for testing the proposed technique. All simulations were performed using the MATLAB/SIMULINK [11].

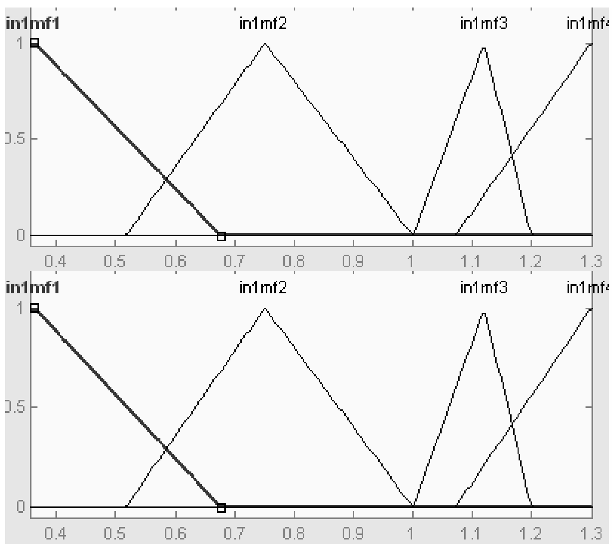

Fig.3 MFs of two inputs of controller in proposed technique

Performance evaluation of the ANFPSS was done by applying a large disturbance caused by a three-phase fault to ground on different positions and in various condition of load level and time delay of protection system.

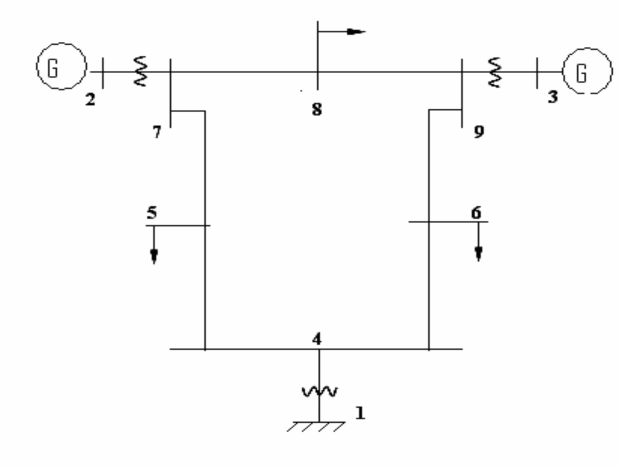

Fig.4 3-Machine 9-Bus Power System

Some different simulations are done and illustrated bellow:

4.1 Case 1:
A 3-phase to ground (3PG) fault was applied to bus 6. In this case the load level is in normal condition and the main protection system can operate in the minimum time. The results are shown in Fig (5) to Fig (8).

4.2 Case 2:
A 3PG fault was applied to bus numbered 8 and the power system has % 20 overloads. The results are shown in Fig (9) to Fig (12).

4.3 Case 3:
A 3PG fault was applied to bus numbered 2 and the main protection system failed to clear the fault, so the backup protection operates with a normal time delay. Therefore in this case fault clearing time is longer than the two previous cases. The results are shown in Fig (13) to Fig (16).

5. Conclusions
This paper described an ANFIS based power system used for damping oscillation in Multi-Machine power systems. In this method FPSS, which uses Takagi-Sugeno type FLC, is trained in a systematic approach to set on proper parameters. The parameters of proposed PSS (such as MFs and Fuzzy IF-THEN rules) are tuned off-line using an adaptive network; consequently the proper damping signal can be generated in wide range condition of power system in on-line operation.
The proposed PSS is tested on a 3-Machine 9-bus system under different conditions such as change on load level, change on position of fault and the time of fault clearing. The simulation results and ANFPSS's responses to various disturbances have demonstrated that the proposed ANFPSS can effectively enhance the damping of low frequency oscillations.

6. References

[1] N. Hossein Zadeh, A. Kalam, "*PERFORMANCE OF A SELF-TUNED FUZZY-LOGIC POWER SYSTEM STABILISER IN A MULTIMACHINE SYSTEM*" School of Engineering and Science Monash University, Malaysia.
[2] A.Sree, V.Ghadir, R.M.Abdelrahman, "*AN ADAPTIVE NEURO FUZZY POWER SYSTEM STABILIZER FOR DAMPINGINTER-AREA SCILLATIONS IN POWER SYSTEMS*", 2001.
[3] P.Hoang, K.Tomsovic, "*DESIGN AND ANALYSIS OF AN ADAPTIVE FUZZY POWER SYSTEM STABIZER*", IEEE Transaction on Energy Conversions, Vol. 11, No. 2, June 1996.
[4] N. Hossein Zadeh, A. Kalam, ' *A Direct Adaptive Fuzzy Power System Stabilizer*' , Proceeding of the 4th Conference on Advances in power System Control, operation and Management, APSCOM-97, Hong Kong, Nov. 1997.
[5] M.chetty, N.Trajkoski, '*A Discrete Mode Fuzzy Power System Stabilizer*', Monash University, Australia.
[6] M.A.Hasan, O.P.Malik, '*Implementation and Laboratory Test Results for a Fuzzy Logic Based Self-Tuned Power System Stabilizer*', IEEE/PES Summer Meeting, seattle, July 1992.
[7] J.Lu, M.H.Nehrir, D.A.Pierre, '*A Fuzzy Logic-based Adaptive Power System Stabilizer for Multi-Machine Systems*', IEEE, 2000.
[8] M.Hashem, H.Eghbali, ' *A neuro-fuzzy power system stabilizer with self-organizing map for Multi-machine systems*' , Proceeding of IEEE Power Engineering Society Transmission and Distribution Conference, Vol. 2, 2002, pp. 1219-1224.
[9] D.Menniti, A.Burgio, A.Pinnarelli, V.Principle, N.Scordino ,N.Sorrention, '*Damping Oscillation Improvement BY Fuzzy Power System Stabilizers tuned by Genetic Algorithm*' , 14th PSCC, Sevilla, 2002.
[10] JShing and R.Jang,"*ANFIS: Adaptive-network based fuzzy inference system,*"IEEE Trans., Vol. 23, MayIJune 1993, pp 665-685.
[11] www.mathworks.com
[12] A.Harrir, O.P.Malik, 'Implementation *and real*

time studies with a Self-Learning Adaptive-Network Based Fuzzy Logic PSS', 14th PSCC, Sevilla, 2002.

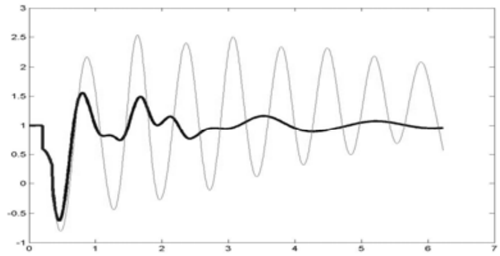

Fig.5 Variation of P_{g2} (case 1)

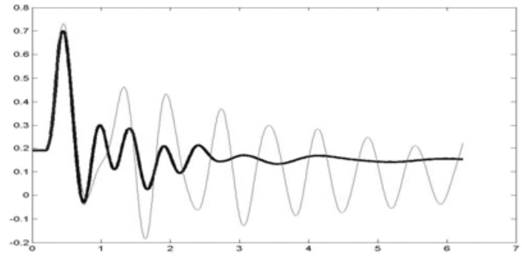

Fig.6 Variation of δ_2 (case 1)

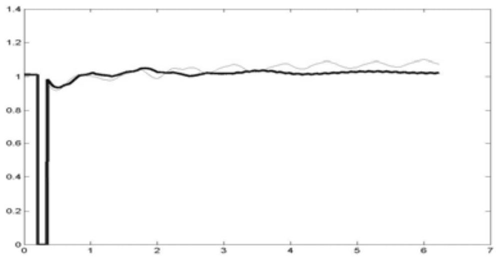

Fig.7 Variation of V_6 (case 1)

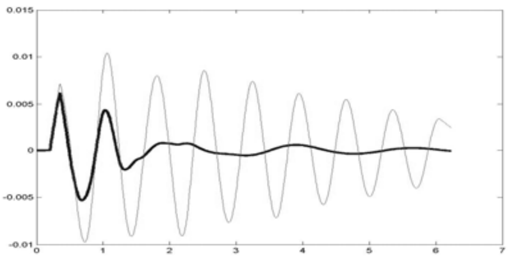

Fig.8 Variation of ω_2 (case 1)

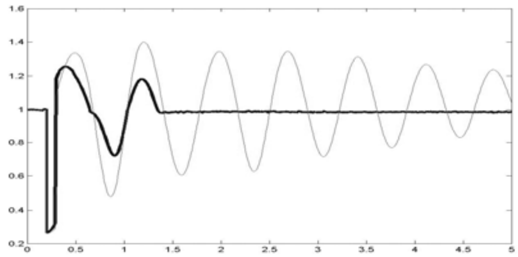

Fig.9 Variation of P_{g2} (case 2)

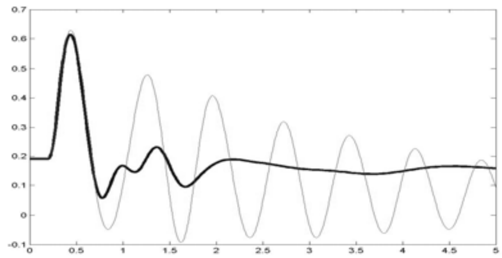

Fig.10 Variation of δ_2 (case 2)

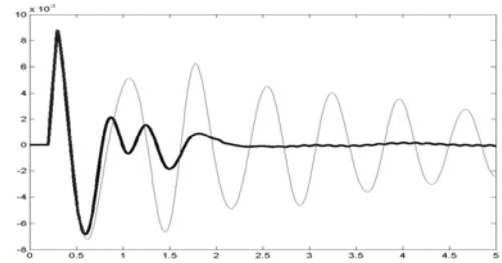

Fig.11 Variation of ω_2 (case 2)

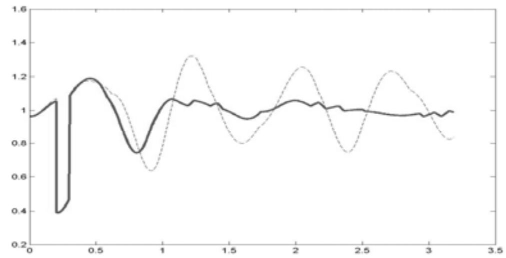

Fig.12 Variation of P_{g3} (case 2)

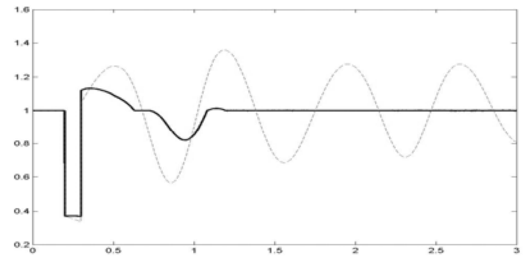

Fig.13 Variation of δ_2 (case 3)

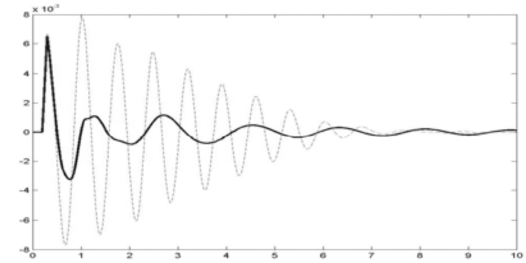

Fig.14 Variation of ω_2 (case 3)

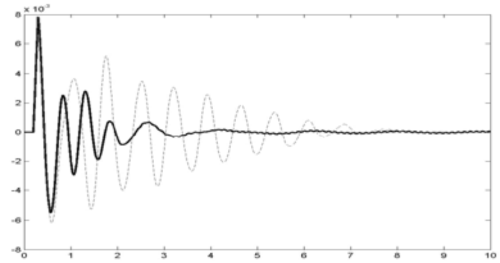

Fig.15 Variation of δ_3 (case 3)

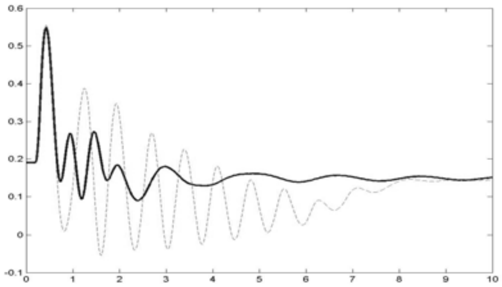

Fig.16 Variation of ω_3 (case 3)