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Comparative Performance of Neuro-Fuzzy PSS Architectures with Adaptive Input Link Weights and Nonlinear Functions

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Abstract: Based on a Neuro-Fuzzy Controller (NFC) architecture, two approaches are presented for the design of a Power System Stabilizer (PSS) with adaptive input scaling. In the first approach, input link weights (ILWs) are introduced and the NFC is made adaptive by the online modification of the ILWs and the consequent parameters (CPs) through the gradient descent method. In the second approach, nonlinear functions (NLFs) are used in the first layer of the NFC and both NLFs and CPs are modified online by using a hybrid adaptation process. Comparison studies on a one machine-infinite bus system and a multi-machine power system show the ability of the proposed PSSs to improve the system dynamic performance.

1. INTRODUCTION

For many years, the Power System Stabilizer (PSS) based on a transfer function and a linear model of the plant at some operating point has been widely used for damping power system oscillations. Due to dynamic and nonlinear characteristics of power systems, this conventional PSS (CPSS) generally provides acceptable performance only over a limited range of operating conditions.

To enhance the performance and stability of power systems for a wide range of conditions of operation, fuzzy logic (FL) and artificial neural nets (ANN) techniques have been recently proposed in the literature for PSS design. In particular, the approaches that include online tuning of the controller's parameters show great potential.

A fuzzy logic controller (FLC) based on an adaptive network architecture provides a suitable medium to optimize its parameters by applying a gradient descent training algorithm (Jang *et al*., 1997). Therefore, it has been used to develop PSSs with enhanced performance and increased robustness (Hariri and Malik, 1996; You *et al*., 2003; Barton, 2004). The common practice in the designs has been the tuning of input membership functions (IMFs) and consequent parameters (CPs) of the rules. However, it is well recognized that the scaling factors (SFs) also play a very important role in the successful design of the controller (Passino and Yurkovich, 1998). Due to their global effect on all the control rules in a rule base, SFs have been given the highest priority among various tuning parameters (Zheng, 1992; Reznik, 1997). Nevertheless, they have received little attention in the design of adaptive PSSs based on FLCs.

In this work, based on a Neuro-Fuzzy Controller (NFC) architecture, two approaches are presented to design an Adaptive PSS with modifiable input scaling. The performance of these two adaptive neuro-fuzzy PSSs is examined over various operating conditions and disturbances in a single machine-infinite bus system and a multi-machine power system.

2. FLC AND SFs

From a control design point of view, SFs represent the gain applied to the input and output of a system. From the knowledge representation perspective, they provide context information and define the operating range of variables in a particular application (Gudwin *et al*., 1998; Magdalena, 1997). Since the output scaling factor is generally determined by physical limits of the control signal applied to a specific plant, attention here is given to the input scaling factors (ISFs) as they have the most influence on basic sensitivity of the controller with respect to the optimal choice of operating ranges for the input variables (Reznik, 1997; El-Geliel and El-Khazendar, 2003).

The adjustment of SFs represents a simple solution to find the fuzzy sets that best fit the linguistic terms they are associated with to obtain satisfactory models or controls (Gudwin *et al*., 1998). Both linear and nonlinear scaling can be considered. Linear scaling provides a linear context adaptation and is similar to how an accordion operates. This approach does not change the shape or position of MFs but scales them proportionally by defining new bounds of the operating interval as shown in Fig. 1. For fuzzy concepts represented by base MFs in a reference universe, e.g. {-1, 1}, nonlinear scaling is able to keep this normalized interval by modifying the relative sensitivity of areas within it. Fig. 2 illustrates how the shape of MFs is changed by using a very simple nonlinear function given by:

$$y = f(x) = sign(x) * |x|^{\alpha} \tag{1}$$

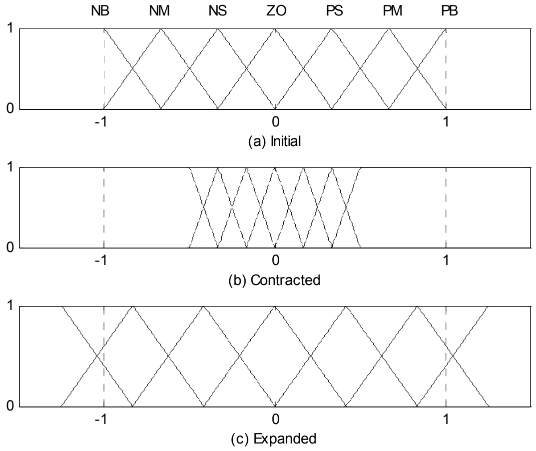

Fig. 1. Operating range with linear scaling.

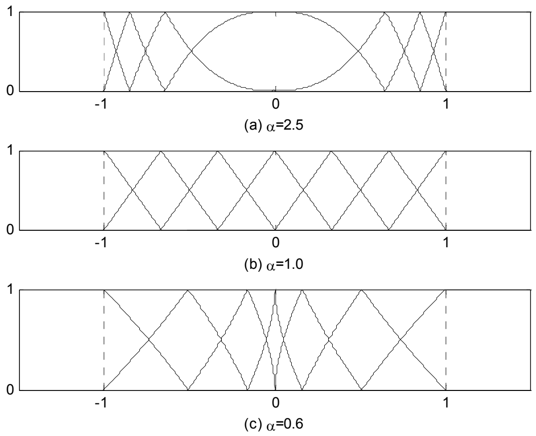

Fig. 2. Operating range with nonlinear scaling.

3. ADAPTIVE NEURO-FUZZY PSS (ANFPSS) ARCHITECTURE

The proposed PSSs are based on the NFC architecture described by Jang *et al*., 1997. For the first approach in this work, adaptive link weights, w_1 and w_2, are inserted between the ISFs and the input layer of that NFC architecture, as shown in Fig. 3 (a). For the second alternative, the NLF given in (1) is integrated in the first layer of the network, as illustrated in Fig. 3 (b).

The inputs of the NFCs are the speed deviation $\Delta\omega$ and its derivative $\Delta\dot{\omega}$. The output is the control signal *Vpss*. K_1 and K_2 are the ISFs, and K_3 is the SF for the output. The MFs shown in Fig. 1(a) are used for each input with the commonly used associated fuzzy sets. The firing strength of each rule is calculated using the *"*product*"* operation. With seven fuzzy singletons for the output, the rule base is given in Table 1.

4. CONTROL STRUCTURES

The control system structure (CSS) for each approach is shown in Figs. 4 and 5, respectively. The main components of the CSS1 in Fig. 4 are an adaptive neuro-identifier (ANNI) to track the dynamic characteristics of the plant, and the NFC with ILWs (ANFPSS1). The CSS2 in Fig. 5 consists of an ANNI, the NFC with NLFs at input layer (ANFPSS2), a FIS

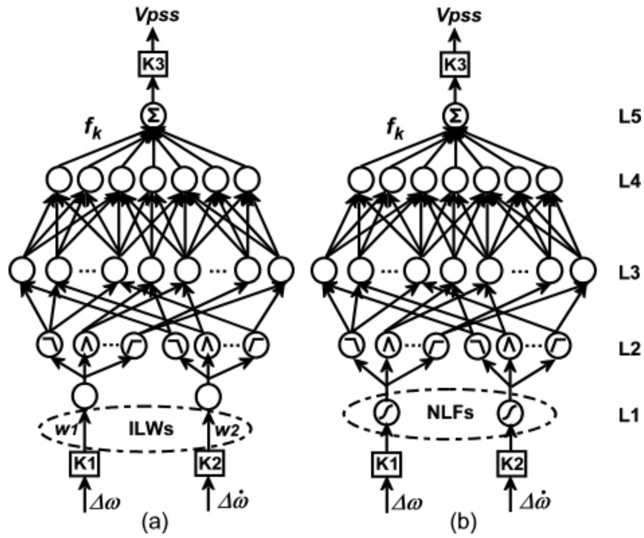

Fig. 3. NFC with: (a) ILWs and NLFs.

Table 1. Rule base

$\Delta\dot{\omega}$	$\Delta\omega$						
	NB	NM	NS	ZO	PS	PM	PB
NB	-1.0	-1.0	-1.0	-1.0	-0.66	-0.33	0.0
NM	-1.0	-1.0	-1.0	-0.66	-0.33	0.0	0.33
NS	-1.0	-1.0	-0.66	-0.33	0.0	0.33	0.66
ZO	-1.0	-0.66	-0.33	0.0	0.33	0.66	1.0
PS	-0.66	-0.33	0.0	0.33	0.66	1.0	1.0
PM	-0.33	0.0	0.33	0.66	1.0	1.0	1.0
PB	0.0	0.33	0.66	1.0	1.0	1.0	1.0

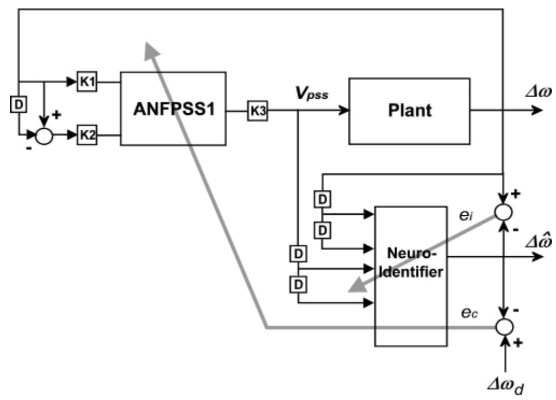

Fig. 4. Control system structure 1 (CSS1).

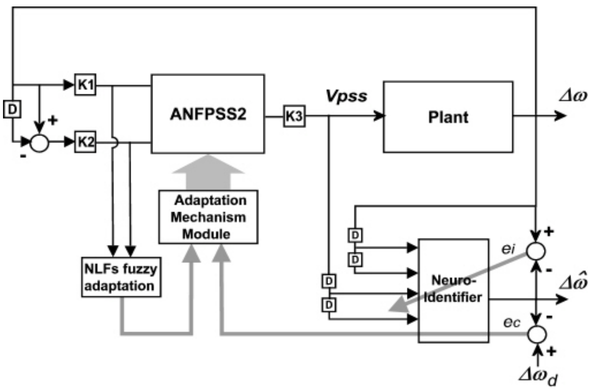

Fig. 5. Control system structure 2 (CSS2).

to adjust the shape of the NLFs, and an adaptation module to coordinate and apply the adjustments required by the hybrid adaptation process described in the next section.

4.1 Adaptive Neuro-Identifier

A neural network based plant model with online adaptation has the capability to cope with plant complexity, uncertainty, nonlinearity and variations with time (Jha and He, 2004). Besides, it has been proven that by using a series-parallel model a feed-forward network of a single layer with a finite number of nodes can implement any continuous nonlinear function (Nguyen and Widrow, 1990). For the proposed configurations, as the ANNI simply functions as a black box, there is no need to use a fuzzy system as in Hariri and Malik, 1996.

A feed-forward network with three layers is considered. The input to the ANNI is:

$$[\Delta\omega(k), \Delta\omega(k-1), ..., \Delta\omega(k-n+1), \quad Vpss(k-1), Vpss(k-2), ...Vpss(k-m)]. \tag{2}$$

where $m=n=3$. The output is the predicted speed deviation $\Delta\hat{\omega}(k)$. Applying the gradient descent method (Haykin, 1999), the weights of the ANNI are updated to minimize the cost function:

$$J_i(k) = \frac{1}{2} e_i(k)^2 = \frac{1}{2}\left[\Delta\omega(k) - \Delta\hat{\omega}(k)\right]^2 \tag{3}$$

4.2 ANFPSS

Despite the advantages an NFC offers (Jang *et al*., 1997; Linkens and Nyongesa, 1995), its design may significantly hinder its application. There are many parameters that influence its control surface and similar effects can be reached by modifying different sets of parameters (Reznik, 1998). Multiple adaptation efforts also make optimal regulation more difficult (Janabi-Sharifi and Liu, 2005). If a large number of parameters are to be adjusted directly, the adaptation process can involve extensive computations in such a way that the optimization can only be done offline. However, without an online self-adaptive mechanism, the NFC's performance might be unsatisfactory to changes in the system operating conditions.

In this work, only two sets of parameters are selected to be modified online and make the controller adaptive: ILWs and CPs for ANFPSS1, and sensitivity of NLFs and CPs for ANFPSS2.

Parameters sets of the ANFPSS1 are updated according to the error back-propagation method and the cost function:

$$J_c(k) = \frac{1}{2} e_c(k+1)^2 = \frac{1}{2}\left[\Delta\hat{\omega}(k+1)\right]^2 \tag{4}$$

As for the ANFPSS2, the same adaptation method is applied to its CPs. However, the sensitivity parameter α of the NLF in (1) is determined by a FIS with an input signal computed from the following expression:

$$R = \sqrt{(\Delta\omega_N)^2 + (\Delta\dot{\omega}_N)^2} \tag{5}$$

It is clear that the intensity of disturbance is proportional to the value of R. Therefore, the rule base of this system is designed based on the following reasoning:

- If R is very big, it means that the states are far away from the origin. Consequently, a relatively large control action is required such that the plant can be pushed back to the desired point. This effect can be obtained by assigning a small value to α in (1), with $0.0 < \alpha \le 1.0$.
- If R is getting close to the centre, a relatively small value of α will produce a large control signal that could induce oscillations around the steady-state operating point. Therefore, α should be big enough to reduce this undesired effect.

With five triangular MFs for the input R and five fuzzy singletons for the output α, the rule base in Table 2 is built.

Table 2. Rule base for fuzzy adaptation

R	*VS*	*S*	*M*	*B*	*VB*
α_l	*VB*	*B*	*M*	*S*	*VS*

5. PARAMETER SET-UP AND ADAPTATION PROCESS

The ANNI is composed of 6, 8 and 1 neurons. It was first trained off-line and then integrated in the presented control schemes, where its weights are updated online. The ANNI provides a dynamic model of the plant to adjust parameters of the NFC. The ANFPSSs consist of five layers with 2, 14, 49, 7, and 1 nodes associated with each layer. K_1 and K_2 are fixed to approximately the inverse of the maximum values observed in simulation for $\Delta\omega$ and $\Delta\dot{\omega}$, respectively. K_3 is set by the output limits of the controllers. CPs are initialized as shown in Table 1. The initial value for w_1 and w_2 in Fig. 3 is *1.0*. The initial value of α for the NLFs in Fig. 4 is also *1.0*.

With regard to the FIS for the adaptation of input NLFs in ANFPSS2, MFs for R are evenly distributed in the range {0, 1}. Distribution of the fuzzy singletons for the output was determined by analyzing the influence of the parameter α in the controller performance. From that, a three-phase to ground short-circuit test and a 0.10 p.u. step change in the mechanical torque under an operating condition of power at 0.90 p.u and 0.85 p.f. lag were selected to compute them. First, applying the reasoning depicted in Table 2 with a three-phase short-circuit test, α is reduced to the point where the cost function of the controller J_c stops decreasing and then starts to increase. The value obtained here was assigned to *VS*. The same procedure was used with a 0.10 p.u. step change in the mechanical torque and the resultant value was given to *B*. Between *VS* and *B*, *M* and *S* were distributed evenly and the fuzzy singletons in Table 3 were determined. It is important to mention that the CPs of the ANFPSS2 were fixed to their initial values during this stage.

5.1 ANFPSS1 Parameter Adaptation

The adaptation process involves the following steps:

Table 3. Fuzzy singletons for α

$\alpha_1 = \alpha_2$				
VS	*S*	*M*	*B*	*VB*
0.65	*0.70*	*0.75*	*0.8*	*1.0*

- At time step k, sample $\Delta\omega(k)$.
- Use $\Delta\omega(k)$ and $\Delta\hat{\omega}(k)$ to update the weights of the ANNI and minimize $J_i(k)$.
- Compute the predicted speed deviation $\Delta\hat{\omega}(k+1)$.
- Based on $\Delta\hat{\omega}(k+1)$, work with one set of parameters between ILWs and CPs of the ANFPSS1 to minimize $J_c(k)$. For example, if ILWs are modified at time step k, then CPs will be updated at instant $k+1$.
- Compute the output of the ANFPSS1 for time step k, apply it to the plant, and repeat the process.

5.2 ANFPSS2 Parameter Adaptation

In this case, the steps involved in the adaptation process are:

- At time step k, $\Delta\omega(k)$ is sampled and $\Delta\dot{\omega}(k)$ is derived.
- Using $\Delta\omega(k)$ and $\Delta\hat{\omega}(k)$, the weights of the ANNI are updated to minimize $J_i(k)$.
- The output of the controller is calculated using the value of $\alpha_l(k)$ determined by the fuzzy adaptation system.
- $\Delta\hat{\omega}(k+1)$, the predicted speed deviation, is computed.
- The error between the desired and the predicted plant output is determined and then back-propagated through the ANNI and ANFPSS2 to update the CPs and minimize $J_c(k)$.
- The output of the ANFPSS2 for time step k is computed and then applied to the plant. The adaptation process will start over for time instant $k+1$.

6. SIMULATION STUDIES

6.1 Single machine-infinite bus system (SMIBS)

Schematic diagram of the SMIBS generating unit connected to a constant voltage bus through two parallel transmission lines is shown in Fig. 7. Differential equations for the seventh-order generator model, transfer functions of the governor, AVR, CPSS, as well as the system parameters are given in He and Malik, 1997.

For comparison, a CPSS based on the phase-lead compensation technique (Kundur, 1994) with the following transfer function was designed:

$$V_{pss}(s) = K_{pss}\left(\frac{sT_w}{1+sT_w}\right)\left(\frac{1+sT_1}{1+sT_2}\right)\left(\frac{1+sT_3}{1+sT_4}\right)\Delta\omega(s) \quad (6)$$

Parameters for the CPSS are:

K_{pss}=28, T_1=0.021, T_2=0.0021, T_3=T_1, T_4=T_2, T_W = 10.

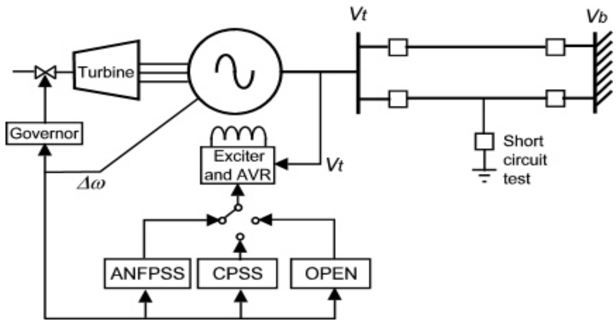

Fig. 6. SMIBS configuration.

Simulations results for the following operating conditions and disturbances are presented:

a) P=0.70 p.u., 0.85 p.f. lag. A 0.05 p.u. step increase in torque is applied at 1 *s* and then removed at 5 *s*. The CPSS was tuned at this operating point. See Fig. 7.

b) P=0.30 p.u., 0.90 p.f. lead. A 0.10 p.u. step increase in reference voltage is applied at 1 *s* and then removed at 5 *s*. See Fig. 8.

c) P=0.95 p.u., 0.90 p.f. lag. A three phase to ground short circuit at the middle of one transmission line is applied at 1 *s*, cleared 60 *ms* later by the disconnection of the faulted line, and then successfully re-closed at 5 *s*. See Fig. 9.

6.2 Multi-machine power system (MMPS)

The MMPS configuration used for the study is shown in Fig. 10. It can be viewed as a two-area system, with generators G3, G2 and G5 forming one area, and G1 and G4 forming another area. The two areas are connected together through a tie line between buses 6 and 7. System's operating conditions and parameters are given in Elmetwally and Malik, 1996.

a) *Step increase in mechanical torque*. With PSSs installed on generators G1, G2 and G3, system response to a 0.10 p.u. step increase in the mechanical input torque reference of G3 at 1 *s* is given in Fig. 11. It shows that both local and inter-area modes of oscillation are damped effectively. The CPSSs on all three generators were designed individually to match the characteristics of each generator; however, the same ANFPSS was applied to all three generators.

b) *Three phase to ground fault test*. At 1 *s* a three phase to ground fault is applied at the middle of one transmission line between buses 3 and 6. It is cleared 90 *ms* later by the disconnection of the faulted line. Figure 12 shows the response of the system with PSSs installed on G1, G2 and G3.

7. ANFPSS1 AND ANFPSS2 COMPARISON

The proposed ANFPSSs are based on the online adaptation of input scaling and consequent parameters of the controllers. Some points of comparison between the two approaches are:

- *Performance*. Simulations results show that the proposed approaches have good damping ability for different operating conditions and disturbances. The ANFPSS2 is able to provide slightly better results in terms of over-

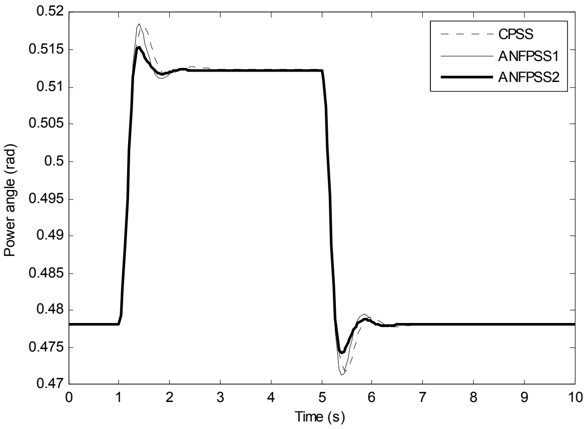

Fig. 7. System response for test (a) in SMIBS.

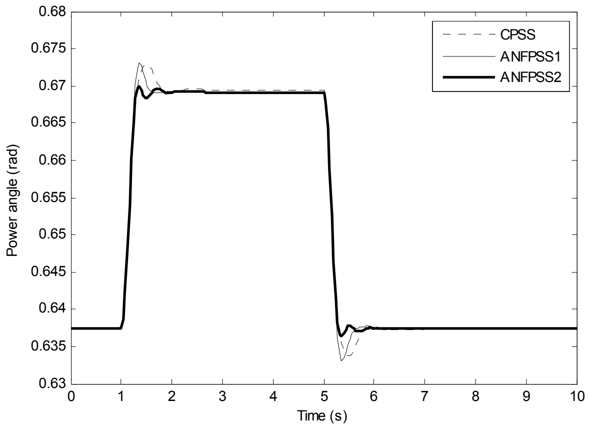

Fig. 8. System response for test (c) in SMIBS.

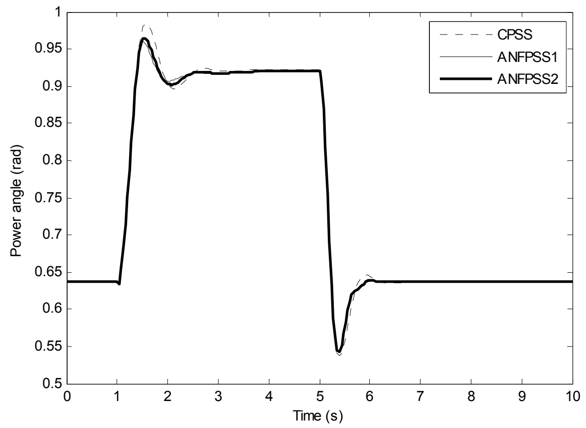

Fig. 9. System response for test (d) in SMIBS.

shoot. The settling time is practically the same for both alternatives.

- *Controller's parameter adaptation process*. Only the gradient descent technique is used to adjust both ILWs and CPs of the ANFPSS1. However, the adaptation process alternates and deals with them in such a way that every set of parameters is updated at different sampled instants. The ANFPSS2 uses a hybrid adaptation method by applying the gradient descent technique and a fuzzy inference mechanism. Both alternatives contribute to enhancing the computational effort involved, which is important for real time applications.

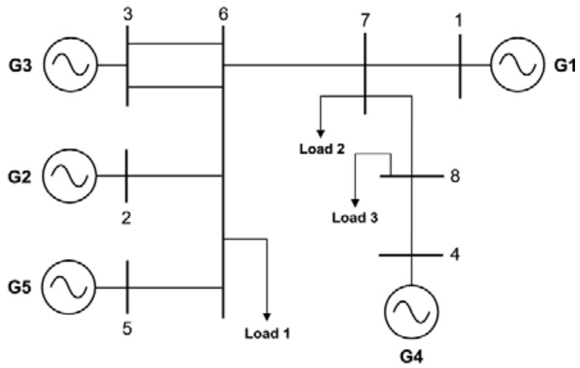

Fig. 10. MMPS configuration.

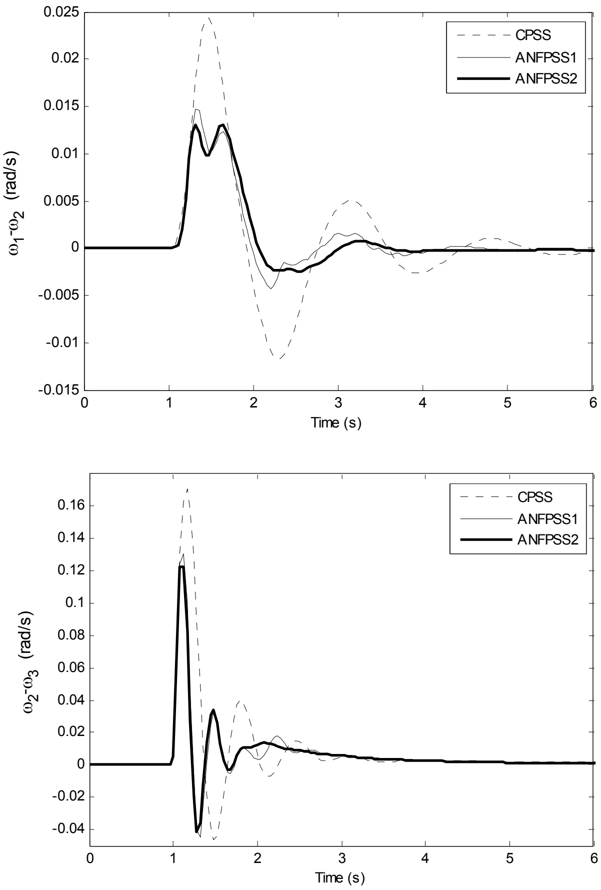

Fig. 11. Step increase in mechanical torque.

- *Number of controller's parameters*. The proposed PSSs enable the designer to work with a small number of controller's tuning parameters, regardless of the number and shape of input membership functions. In this regard, at every sampling instant a maximum of two parameters are updated in the ANFPSS1 and three in the ANFPSS2.
- *Design methodology*. For both approaches, the ANNI was first trained off-line and then integrated in the control structures CSS1 and CSS2 for online adaptation. Apart from this, no more offline computations were required to implement the ANFPSS1. On the other hand, for determining the parameters of the fuzzy adaptation

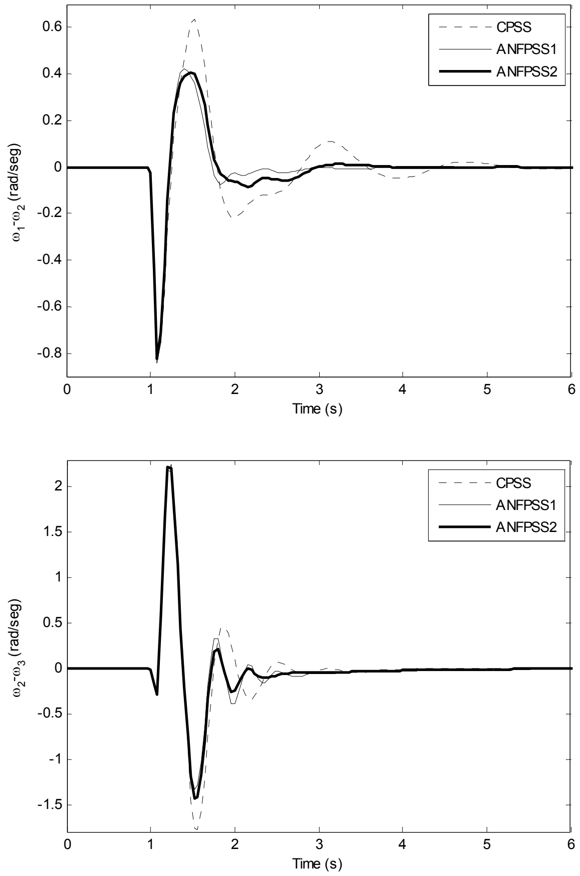

Fig. 12. Three phase to ground fault test.

system used by the ANFPSS2 additional offline computations were required before its final implementation.

8. CONCLUSIONS

At every sampling instant, the ANFPSS1 deals with a smaller number of controller's tuning parameters than the ANFPSS2. However, this is counterbalanced by the way each approach updates its parameters. Because of the additional offline effort in the ANFPSS2, the design process of the ANFPSS1 is faster. However, for the online implementation, the ANFPSS2 is preferred because it does not require computation of derivatives up to the inputs of the controller. Besides, the ANFPSS2 may provide a better performance than the ANFPSS1. Since the performance of both approaches is good in comparison, any of them can be used for improving the damping of power systems oscillations.

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