J. Automation & Systems Engineering 12-1 (2018): 1-13

Regular paper

JASE
Journal of Automation
& Systems Engineering

Nonlinear Adaptive Sliding Mode Power System Stabilizer

K. Saoudi[1], Z. Bouchama[2], M. Ayad[1], M. Benziane[1] and M. N. Harmas[3]

[1]Department of electrical engineering, University of Bouira Bouira, Algeria, saoudi_k@yahoo.fr.
[2]Department of sciences and technology, University of Bordj Bou Arreridj, Bordj Bou Arreridj, Algeria.
[3]Department of electrical engineering, University of Setif1, Setif, Algeria

***Abstract-** In this paper, a nonlinear adaptive power system stabilizer based on sliding mode control methodology is proposed to handle with the large uncertainties and severe types of disturbances. The proposed approach is developed to make the system dynamics insensitive to uncertainties and disturbances such that power system states start, move and stay on the switching surface toward the equilibrium point that guarantees convergence in small time and eliminates the reaching phase. Moreover, the gains of the controller are optimized using Particle Swarm Optimization approach. The PI sliding mode control method and the Lyapunov synthesis approach are incorporated in an indirect adaptive type-2 fuzzy control scheme such that the derived controller is robust adaptive which closely tracks any changes in power system operating conditions and guarantees stability convergence. A benchmark model of a two-area four-machine power system is used to evaluate the performance of the proposed stabilizer. Simulation results demonstrate the effectiveness and robustness of the proposed stabilizer in damping inter-area oscillations compared with those obtained with a conventional PSS and with an adaptive type-2 Fuzzy PSS. Furthermore, it clearly shows the superiority of the proposed approach.*

Keywords: Adaptive fuzzy control, Sliding mode control, Power Systems.

Article history: Received 21 December 2017, Accepted 4 February 2018

1. INTRODUCTION

The stability of power systems is one of the most important aspects that need to be addressed to ensure a reliable and secure supply of electricity. Power System Stabilizers (PSSs) have been widely used to damp electromechanical oscillations and to enhance dynamic stability in power system. The design of power system stabilizer based on linearized models of complex nonlinear systems, may no longer be satisfactory when the changes in operating conditions or system topology and parameters. The nonlinear control techniques are getting more attention of researchers and also being used in to design power system applications.

In the last decade, considerable efforts have been directed towards the applied of Artificial Intelligence Techniques and Evolutionary Algorithms to the design the nonlinear adaptive stabilizing controllers in a large number of research works that grasp the merits of adaptive and intelligence techniques and overcomes theirs drawbacks. There are widely applied research works: Artificial Neural Network [1-2], Fuzzy Logic [3-4], Genetic Algorithms [5] and Particle Swarm Optimization [6]. Merging more than one Artificial Intelligence

Technique is also common in the literature [7–10]. This technique does not guarantee performance and robustness since cancellation is practically imperfect.

Sliding Mode Control (SMC) approach has been reported as one of the most effective control methodologies for nonlinear power system applications [11-12] in improving power system stability and robustness due to its low sensitivity to parameter variations and external disturbances. Nowadays, some researches has attracted the attention of many researchers to guarantee robustness in adaptive intelligent techniques [13-14]. The main idea behind this control scheme is to approximate unknown nonlinear functions of the power system dynamics model by adaptive fuzzy system and to synthesize the control law using the SMC approach. Nevertheless, before the system gets in the sliding mode, the dynamic performance may be degraded because it is not well sensitive against the wide domain of variations of the operating condition, the system parameters and disturbances size. This means, the invariance property is not guaranteed during transient phase of creating a situation known as reaching phase.

In this research work, a nonlinear adaptive power system stabilizer based on sliding mode control methodology is proposed for damping oscillations of interconnected multi-machine power systems. The main contributions of this research work are the following: (i) The improvement of the robustness and the transient performance by removal of transient phase that guarantees convergence in small time, eliminates the reaching phase and the chattering phenomenon, (ii) The sliding mode controller is extended based on an indirect adaptive type-1 fuzzy control to use type-2 fuzzy system to approximate system dynamics, (iii) The parameters of the controller are tuned using Particle Swarm Optimization (PSO) approach to get a good damping characteristics, (iv) The robustness and the stability properties of the resulting closed-loop system is proved in the sense of Lyapunov.

2. PROBLEM FORMULATION

In the design of the power system controller proposed in this paper, let $x_1 = \Delta\omega =$ the speed deviation and $x_2 = \Delta P = P_m - P_e$ the accelerating power. It is possible to represent the *i*-th machine of a multi-machine power system in the following nonlinear state-space equations form:

$$\begin{aligned} \dot{x}_1 &= a x_2 \\ a\dot{x}_2 &= f(x_1, x_2) + g(x_1, x_2)u, \qquad y = x_1 \end{aligned} \tag{1}$$

Where, $a = 1/2H$ and $\underline{x} = [x_1, x_2]^T \in R^2$ is a measurable state vector, H is the per unit machine inertia constant PSS output u represents the supplementary control signal to be designed and $y = \Delta\omega$ is the considered output while $f(\underline{x})$ and $g(\underline{x})$ are nonlinear system functions which are assumed to be unknown and $g(\underline{x}) \neq 0$ in the controlled region. Equation (1) represents the machine during a transient period after a major disturbance has occurred in the system.

2.1 Sliding mode control design

The control objective is to force y in the system (1) to track a given bounded desired trajectory y_d, under the constraint that all variables involved must be bounded. i.e., The tracing error ($e = y - y_d$), must converge towards zero.

In the following, a brief introduction to classical SMC design method will be discussed. The process of Sliding-Mode Control (SMC) can be divided into two phases, they are: the approaching phase with $s(\underline{x},t) \neq 0$ and the sliding phase with $s(\underline{x},t) = 0$.

In traditional SMC, a switching surface representing the desired system dynamics is constructed as

$$s(\underline{e}) = ke + \dot{e} = \underline{k}^T \underline{e} \tag{2}$$

Where: $\underline{e} = \underline{y} - \underline{y}_d = [e, \dot{e}]^T \in R^2$ and $\underline{k} = [k, 1]^T$ are the coefficients of the Hurwitz polynomial $h(\lambda) = \lambda + k$. The resulting sliding-mode control law consists of the following two parts : $u^* = u_{eq} - u_{sw}$

$$u^* = \frac{1}{g(\underline{x})}\left[-k\dot{e} - f(\underline{x}) - \eta\,\mathrm{sgn}(s) + \ddot{y}_d\right] \tag{3}$$

$$u_{eq} = \frac{1}{g(\underline{x})}\left[-k\dot{e} - f(\underline{x}) + \ddot{y}_d\right] \tag{4}$$

$$u_{sw} = \frac{1}{g(\underline{x})}\left[\eta\,\mathrm{sgn}(s)\right] \tag{5}$$

However, power system parameters for nonlinear functions are not well known and imprecise; therefore it is difficult to implement the control law (3) for unknown nonlinear system model. Not only f and g are unknown but the switching-type control term will cause chattering, in addition, during the approaching phase when the system states move towards the desired sliding surface, the system dynamics during transient phase is sensible to the large uncertainties introduced by variations of system parameters as well as changes of operating and disturbances size and the choosing of the value k to improve system performance. The objective of the approach that we propose in this paper is to resolve the above-mentioned problems.

2.2 Type-2 Fuzzy Logic System

In this section, the type-2 fuzzy logic system used is briefly described. The general structure of a Type-2 Fuzzy Logic System (FLS) is very similar to a Type-1 FLS [15-16], as shown in figure 1; the major structural difference is that the defuzzifier block of a type-1 FLS is replaced by the output processing block in a type-2 FLS which consists of type reduction followed by defuzzification. There are five principal parts in a T2FLS: fuzzifier, rule base, inference engine, type-reducer and defuzzifier.

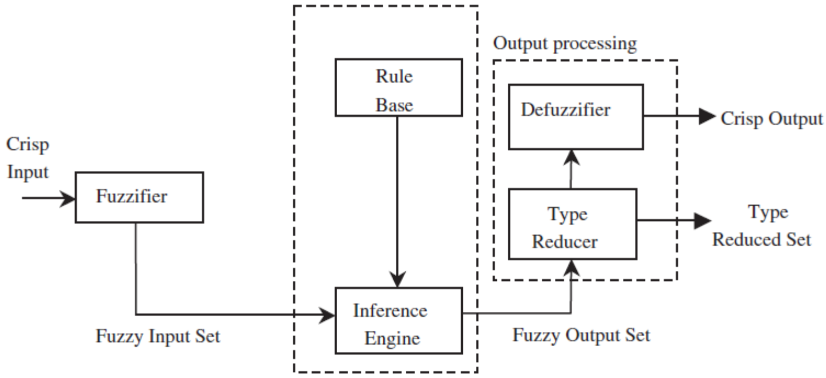


Figure 1. Type-2 fuzzy logic system block diagram.

Fuzzifier

The fuzzifier maps a crisp inputs $x = \left(x_1, ..., x_n\right)$ into fuzzy sets, which can be type-2 fuzzy input sets $\tilde{A}_x$ in general. In this paper, singleton fuzzification method is adopted to map the input variables.

Fuzzy rule base

The Type-2 fuzzy rule base consists of a collection of IF–THEN rules as in the Type-1 case. The l-th rule can be written as

$$R^j : IF\ x_1\ is\ \tilde{F}_1^j\ and \cdots and\ x_n\ is\ \tilde{F}_n^j\ THEN\ y\ is\ \tilde{G}^j \tag{6}$$

where $j = 1, 2, \ldots, M$. M denotes the number of the fuzzy IF-THEN rules, $y \in Y$ is the output, $\tilde{F}_i^j$ and $\tilde{G}^j$ are labels the type-2 antecedent and consequent sets respectively.

Fuzzy inference engine

The inference engine combines rules and gives a mapping from input type-2 fuzzy sets to output type-2 fuzzy sets. In the considered type-2 FLS with singleton fuzzification and meet under minimum or product t-norm, the firing interval F^j of the *j*-th rule is interval type-2 set, which is determined by its left most point and right most point $\underline{f}^j$ and $\overline{f}^j$, as follows:

$$F^j = [\underline{f}^j, \overline{f}^j] \tag{7}$$

The firing interval bounds for the j-th rule of type-2 FLS can be obtained as are defined based on their upper $\bar{\mu}_{\tilde{F}_i^j}(x_i)$ and lower $\underline{\mu}_{\tilde{F}_i^j}(x_i)$ membership functions respectively.

$$\underline{f}^j = \underline{\mu}_{\tilde{F}_1^j}(x_1) * \cdots * \underline{\mu}_{\tilde{F}_n^j}(x_n) = \prod_{i=1}^{n} \underline{\mu}_{\tilde{F}_i^j}(x_i) \tag{8}$$

$$\overline{f}^j = \bar{\mu}_{\tilde{F}_1^j}(x_1) * \cdots * \bar{\mu}_{\tilde{F}_n^j}(x_n) = \prod_{i=1}^{n} \bar{\mu}_{\tilde{F}_i^j}(x_i) \tag{9}$$

Type reduction

From the inference engine the output of a type-2 fuzzy set, a type-reducer is needed before defuzzification to convert type-2 fuzzy sets into type-1. There are many kinds of type reduction methods have been developed, such as centroid, height, modified weight and center-of-sets [15-18]. The center of-sets type reduction is one of the most popular methods that will be used in this paper and can be expressed as

$$Y_{\cos} = \int_{\theta^1} \cdots \int_{\theta^M} \int_{f^1} \cdots \int_{f^M} 1 / \frac{\sum_{j=1}^{M} f^j y^j}{\sum_{j=1}^{M} f^j} \quad (10)$$

where $f^j \in F^j = [\underline{f}^j, \overline{f}^j]$, $y^j \in Y^j = [y_l^j, y_r^j]$

Whereas, in this paper we use interval type-2 FLS. Then $Y_{\cos}$ is the interval set determined with its left end point y_l, and its right end point y_r.

Defuzzification

From the type reduction step, the type reduced set $Y_{\cos}$ is determined by its left most point y_l and right most point y_r. Using the center of gravity, the defuzzified crisp output is given by [16]

$$Y = \frac{y_l + y_r}{2} \quad (11)$$

Where y_l can be expressed as a fuzzy basis function (FBF) expansion, i.e,

$$y_l(\underline{x}) = \frac{\sum_{j=1}^{M} f_l^j y_l^j}{\sum_{j=1}^{M} f_l^j} = \sum_{j=1}^{M} \theta_l^j \xi_l^j(\underline{x}) = \underline{\theta}_l^T \underline{\xi}_l(\underline{x}) \quad (12)$$

where f_l^j denotes the firing strength membership grade contributing to the left most point y_l.

Where $\xi_l^j = \frac{f_l^j}{\sum_{j=1}^{M} f_l^j}$, $\underline{\xi}_l(\underline{x})$ is the FBF vector of *Y*, such that $\underline{\xi}_l(\underline{x}) = \left[\xi_l^1 \ldots \xi_l^M\right]^T$ and $\underline{\theta}_l = \left[\theta_l^1 \ldots, \theta_l^M\right]^T$ is the left-end point of *j*-th consequent type-2 FLS y. Likewise, we have

$$y_r(\underline{x}) = \frac{\sum_{j=1}^{M} f_r^j y_r^j}{\sum_{j=1}^{M} f_r^j} = \sum_{j=1}^{M} \theta_r^j \xi_r^j(\underline{x}) = \underline{\theta}_r^T \underline{\xi}_r(\underline{x}) \quad (13)$$

Where $\xi_r^j = \frac{f_r^j}{\sum_{j=1}^{M} f_r^j}$, $\underline{\xi}_r(\underline{x})$ is the FBF vector of *Y*, such that $\underline{\xi}_r(\underline{x}) = \left[\xi_r^1 \ldots \xi_r^M\right]^T$ and $\underline{\theta}_r = \left[\theta_r^1 \ldots, \theta_r^M\right]^T$ is the right-end point of j-th consequent type-2 FLS y.

The output of the type-2 FLS can be given as follows:

$$Y = \frac{y_l + y_r}{2} = \frac{(\underline{\theta}_l^T \underline{\xi}_l + \underline{\theta}_r^T \underline{\xi}_r)}{2} \tag{14}$$

3. ADAPTIVE TYPE-2 FUZZY SLIDING MODE CONTROL DESIGN PPROACH

In this design approach, we added to sliding surface in Equation (2) the term defined in [19] to make that the system is insensitive during transient phase. Then the sliding surface becomes in the following:

$$S = s(\underline{e}) - \frac{2}{\pi}\left[\frac{\pi}{2} - \operatorname{atan}(t)\right] s(\underline{e}(0)) \tag{15}$$

The time derivative of Eq. (15) can be rewritten as

$$\dot{S} = k\dot{e} + f(\underline{x}) + g(\underline{x})u + \frac{2}{\pi}\left(\frac{1}{1+t^2}\right) s(\underline{e}(0)) - \ddot{y}_d \tag{16}$$

If f and g are known, then we could easily construct the following control law:

$$u^* = \frac{1}{g(\underline{x})}\left[-k\dot{e} - f(\underline{x}) + \frac{2}{\pi}\left(\frac{1}{1+t^2}\right)(\underline{e}(0)) - \eta \operatorname{sgn}(S) + \ddot{y}_d\right] \tag{17}$$

However, f and g are not known, we thus replace $f(\underline{x},t)$ and $g(\underline{x},t)$ by the type-2 fuzzy logic system approximates $\hat{f}(\underline{x} \mid \underline{\theta}_f)$, $\hat{g}(\underline{x} \mid \underline{\theta}_g)$ which are in the form of (14).

$$\hat{f}(\underline{x} \mid \underline{\theta}_f) = \frac{\hat{f}_l + \hat{f}_r}{2} = \frac{1}{2}\left(\underline{\theta}_{fl}^T \underline{\xi}_l(\underline{x}) + \underline{\theta}_{fr}^T \underline{\xi}_r(\underline{x})\right) = \underline{\theta}_f^T \underline{\xi}_f(\underline{x}) \tag{18}$$

$$\hat{g}(\underline{x} \mid \underline{\theta}_g) = \frac{\hat{g}_l + \hat{g}_r}{2} = \frac{1}{2}\left(\underline{\theta}_{gl}^T \underline{\xi}_l(\underline{x}) + \underline{\theta}_{gr}^T \underline{\xi}_r(\underline{x})\right) = \underline{\theta}_g^T \underline{\xi}_g(\underline{x}) \tag{19}$$

In order to avoid the chattering problem, we append a proportional integral PI control term to suppress the chattering action. The inputs and output of the latter are defined as

$$u_p = k_p h_1 + k_i h_2 \tag{20}$$

Where $h_1 = S$, $h_2 = \int S dt$, k_p and k_i are PI control gains. (20) can be rewritten as

$$\hat{p}(\underline{h} \mid \underline{\theta}_p) = \underline{\theta}_p^T \underline{\psi}(\underline{h}) \tag{21}$$

$\underline{\theta}_p = \left[k_p, k_i\right]^T \in R^2$ is an adjustable parameter vector, and $\underline{\psi}^T(\underline{h}) = \left[h_1, h_2\right] \in R^2$ is a regressive vector. Therefore around the sliding surface, control law is introduced as.

$$\hat{u}_P = \begin{cases} \underline{\theta}_p^T \underline{\psi}(\underline{h}) & if\ |s|<\Phi \\ \eta \operatorname{sgn}(S) & if\ |s|\geq\Phi \end{cases} \tag{22}$$

where is Φ the thickness of the boundary layer. The switching term is replaced by a PI control action which changes continuously and will lead to smooth out of the chattering effect when the state is within a boundary layer $|s| < \Phi$. The control action is kept at the saturated value when the state is outside the boundary layer. Hence, we set $|\hat{p}(\underline{h}|\underline{\theta}_p)|=\eta$ when $|s|\geq\Phi$

Hence, the control law becomes:

$$u=\frac{1}{\hat{g}(\underline{x}|\underline{\theta}_g)}\left[-k\dot{e}-\hat{f}(\underline{x}|\underline{\theta}_f)+\frac{2}{\pi}\left(\frac{1}{1+t^2}\right)(\underline{e}(0))-\hat{p}(\underline{h}|\underline{\theta}_p)+\ddot{y}_d\right] \quad (23)$$

Using the control law in (23), then (16) becomes:

$$\begin{aligned}\dot{S}&=k\dot{e}+f(\underline{x})+g(\underline{x})u+\frac{2}{\pi}\left(\frac{1}{1+t^2}\right)(\underline{e}(0))-\ddot{y}_d.\\&=f(\underline{x})-\hat{f}(\underline{x}|\underline{\theta}_f)+(g(\underline{x})-\hat{g}(\underline{x}|\underline{\theta}_g))u-\hat{p}(\underline{h}|\underline{\theta}_p)\end{aligned} \quad (24)$$

The next task is to replace $\hat{f}$ and $\hat{g}$ by type-2 fuzzy logic systems represented in (18)-(19), $\hat{p}$ is given by (21) and to develop adequate adaptation laws for adjusting the parameters vector while seeking a zero tracking error.

Theorem 1. Consider the control problem of the nonlinear system (1). If the control (23) is used, the functions $\hat{f}$, $\hat{g}$ and $\hat{p}$ are estimated by (18), (19) and (21). The closed-loop system signals will be bounded and the tracking error will converge to zero asymptotically if the type-2 fuzzy adaptive laws are chosen as:

$$\dot{\underline{\theta}}_{fl}=\gamma_1 S\,\underline{\xi}_{fl}(\underline{x}) \quad (25)$$

$$\dot{\underline{\theta}}_{fr}=\gamma_2 S\,\underline{\xi}_{fr}(\underline{x}) \quad (26)$$

$$\dot{\underline{\theta}}_{gl}=\gamma_3 S_{gl}(\underline{x})u \quad (27)$$

$$\dot{\underline{\theta}}_{gr}=\gamma_4 S_{gr}(\underline{x})u \quad (28)$$

$$\dot{\underline{\theta}}_{p}=\gamma_5 S\,\underline{\psi}(\underline{h}) \quad (29)$$

Proof. See in [14] proof of the theorem

4. OPTIMAL PARAMETERS SETTINGS OF CONTROLLERS GAINS

4.1 Overview of particle swarm optimization

Similar to evolutionary algorithms, the particle swarm is one of the optimization techniques process that is stochastic in nature. It is developed by Eberhart [20]. PSO is initialized with a population of candidate solutions. This population is called a swarm. Each candidate solution in PSO is called a particle. Each particle is treated as a point in the dimensional problem space. The *i*-th particle is represented as position vector $x_i=(x_{i1},x_{i2},...x_{id})$ in d-dimensional space. The movement of this particle is specified by the velocity vector $v_i=(v_{i1},v_{i2},...v_{id})$. The fitness of each particle can be evaluated according to the objective function of optimization problem. The personal best position found during the search by the *i*-th particle memory of the best position as $p_i=(p_{i1},p_{i2},...p_{id})$. The position of the best personal of the entire swarm is noted as the global best position $p_g = (p_{g1}, p_{g2}, ...p_{gd})$. The velocity and position of each particle are updated as follows:

$$v_{id} = \upsilon . v_{id} + c_1 rand(p_{id} - x_{id}) + c_2 rand(p_{gd} - x_{id}) \quad (30)$$

$$x_{id} = x_{id} + v_{id} \quad (31)$$

Where:

c_1 and c_2 are positive constants, and rand are randomly generated numbers in the range [0, 1], υ is a positive inertia parameter.

To increase the system damping, the optimizing objective function in this paper is based on the integral time absolute error index of the speed deviation of the synchronous generator. This fitness function is defined by:

$$J = \sum_{i=1}^{n} \int_{t_1}^{t_2} t \left| \Delta\omega_i \right| dt \quad (32)$$

Where: t_1 and t_2 are the study time limits and, $\Delta\omega_i$ is the speed deviation of the i^{th} generator.

4.2 Parameters of PSSs and Controllers Gains

The proposed controller and the controllers used for purpose of comparison employs the PSO technique to search for the optimal parameter settings of the given controllers.

- The conventional (CPSS) stabilizer consisting of a stabilizer gain K_{PSS}, washout time constant T_w and Lead-Lag compensators with time constants T_1, T_2, T_3, T_4, and a limiter is used for comparison. The stabilizer transfer function is given by:

$$U_{PSS} = K_{PSS} \left(\frac{sT_W}{1+sT_W} \right) \left(\frac{1+sT_1}{1+sT_2} \right) \left(\frac{1+sT_3}{1+sT_4} \right) \Delta\omega \quad (33)$$

  In this structure, the washout time constants T_w and the time constants T_2 and T_4 are usually prespecified.

- The controller obtained using adaptive Type-2 Fuzzy Controller, has the control law

$$u = \frac{1}{\hat{g}(\underline{x} | \underline{\theta}_g)} \left[-\hat{f}(\underline{x} | \underline{\theta}_f) - \underline{k}^T \underline{e} + \ddot{y}_d \right] \quad (34)$$

Where:

$\underline{k} = [k, 1]^T \in R^2$, the k chosen such as all the roots of the corresponding polynomial are located in the open left half plane .

- In the IAFSM controller, designed using the proposed approach, the gains k of the sliding mode surface such that is a hurwitzian polynomial and PI controller gains k_p and k_i, where the first is proportional and the second proportional integral of the surface.

Through the optimization algorithm, the parameters of the PSSs and the controllers gains of each generator in the multi-machine system are tuned to minimize the selected fitness objective function as shown in (32) in order to improve the system performance response.

5. CASE STUDY AND SIMULATION RESULTS

In this study, the two-area four-machine test power system model [21] shown in Figure 2 is selected for testing the performance of the proposed PSS. This model consists of two fully symmetrical areas linked together by two transmission lines of 220 km length. Each area contains two identical synchronous generators rated 20 kV/900 MVA. All generators are connected through transformers to the 230 kV transmission line and equipped with identical speed governors and turbines, exciters, AVR, and PSS. Under normal conditions, the Area 1 transmits 413 MW active power to the Area 2. This power system is typically used to study the low frequency electromechanical oscillations in a large interconnected system. The data corresponding to the machines, exciters, transmission lines, and loads are given in [21].

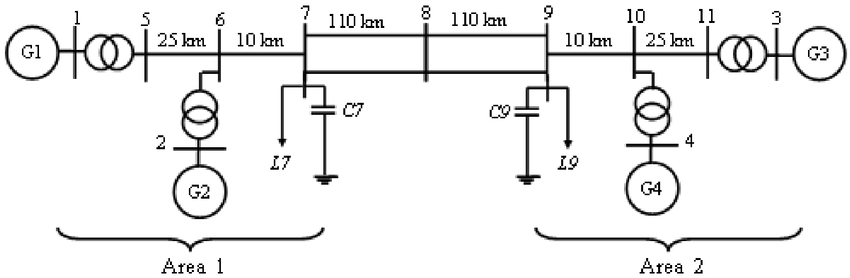
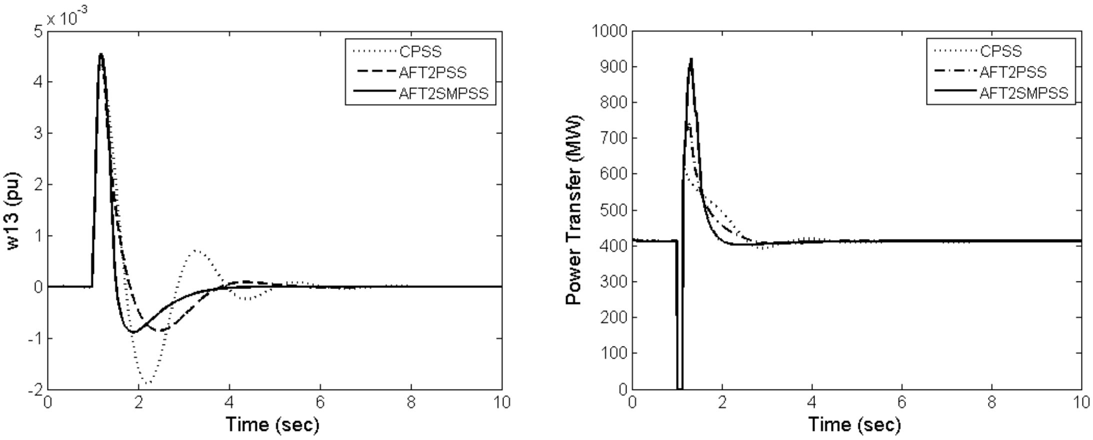


Figure 2 Two area four machine test power system.

The performance of the proposed approach indirect AFSMPSS have been evaluated and compared to those obtained using a conventional (CPSS), using an adaptive type-2 fuzzy power system stabilizer (AFPSS) and using an adaptive type-2 fuzzy synergetic power system stabilizer (AFSPSS). To assess the effectiveness and the robustness of the proposed stabilizer, nonlinear simulations of the test power system are carried out for different faults under two different configurations of system, namely configurations A and B.

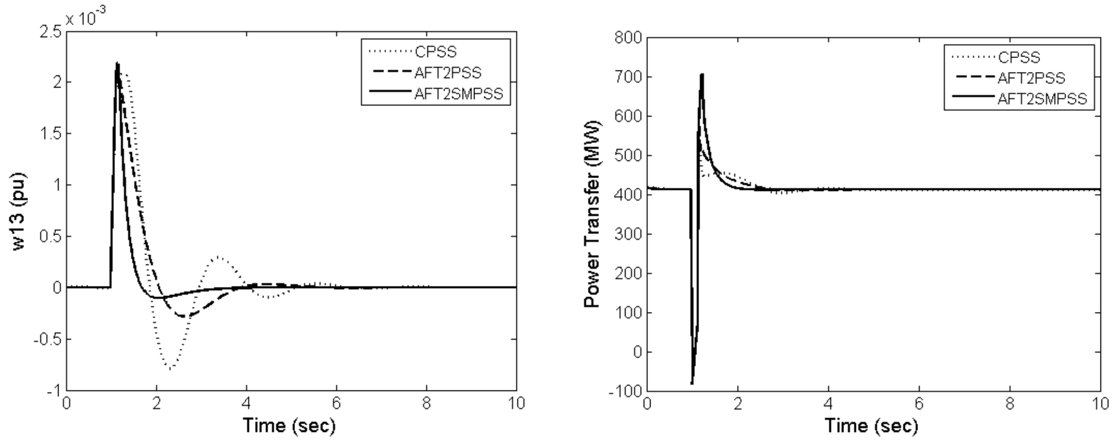
Scenario1: Configurations A

In this scenario, the system configuration has two transmission lines, the performance of the proposed controller under transient conditions is verified by applying a large disturbance of a three-phase fault to ground at three different locations of the tie-line. Location “Bus 8” is at the middle of the tie-line while locations “Bus 7” and “Bus 9” are at locations areas “1” and “2”, respectively. The fault is cleared after 10 cycles by opening the breakers at the ends of the faulty tie-line to disconnect it. The speed difference between generators in area 1 and area 2, with the power transfer from area 1 to area 2 are depicted in Figs. 3–5 respectively. From these figures, it can be clearly seen in all the cases that the system response with the proposed indirect AFT2SMPSS effectively exhibits and confirms superior damping performance of inter-area oscillations in terms of overshooting and settling time compared to the AFT2PSS and CPSS.



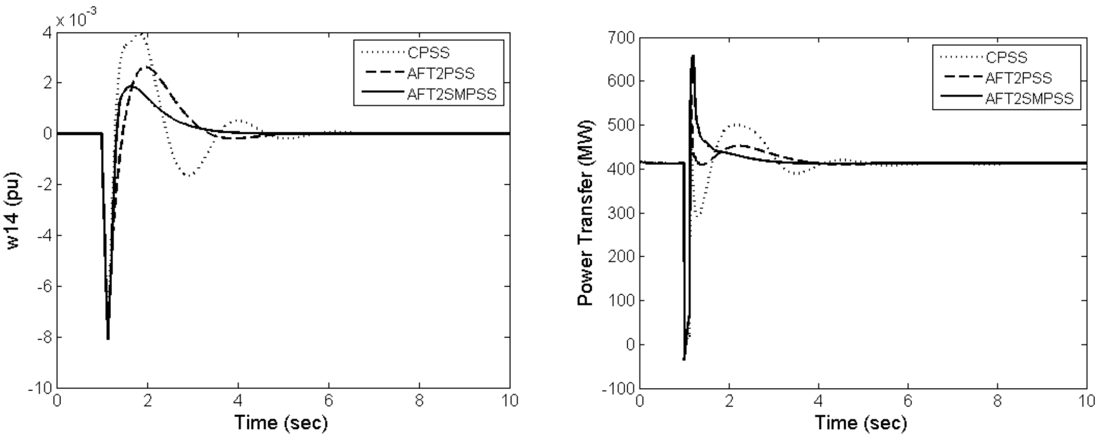
(a) (b)

Figure 3 (a) Gen. 1 swing against Gen. 3 at scenario 1, fault location at the area 1. (b) Power transfer from area 1 to area 2 in scenario 1, fault location at the area 1.



(a) (b)

Figure 4 (a) Gen. 1 swing against Gen. 3 at scenario 1, fault location at the middle of the tie-line. (b) Power transfer from area 1 to area 2 in scenario 1, fault location at the middle of the tie-line



(a) (b)

Figure 5 (a) Gen. 1 swing against Gen. 3 at scenario 1, fault location at the area 2. (b) Power transfer from area 1 to area 2 in scenario 1, fault location at the area 2.

Scenario 2: Configurations B

In this scenario, the system configuration has only one line in between the two buses 8 and 9 is considered i.e. one of the tie-line is disconnected from the system as a contingency. The resulting system can be considered a post-contingency system, with a new configuration which operates at a new operating point. The post-contingency system is subjected to severe disturbance of a 10-cycle three-phase fault to ground at area 1 "Bus 7" of one tie transmission line between buses 7 and 8, cleared by opening the breakers at the ends of the tie-line to isolate it. The system continues to operate with one transmission lines. The system response under this scenario is demonstrated in Fig. 6. It is evident from these results, that the CPSS fails to damp the developed oscillation and to stabilize the system. In both stabilizers AFT2PSS and AFT2SMPSS damp the low frequency oscillations and maintain stability. However, the proposed AFT2SMPSS in the transient response is more robust and provides significantly better damping enhancement in the system oscillations and the oscillations on the power transfer. Note that this superiority in performance is preserved under two different configurations.

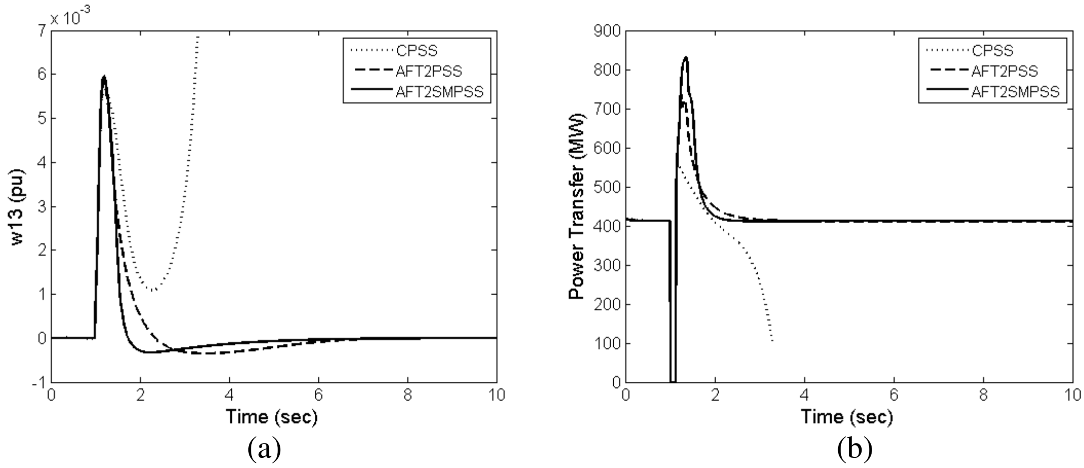


Figure 6 (a) Gen. 1 swing against Gen. 3 at scenario 2, fault location at the area 1. (b) Power transfer from area 1 to area 2 in scenario 2, fault location at the area 1.

6. CONCLUSION

In this paper, an optimal robust indirect adaptive type-2 fuzzy power system stabilizer based on sliding mode control methodology is proposed for damping low frequency inter-area oscillations in multi-machine power systems in the presence of power system's unmodeled dynamics, parametric variations or operating conditions and disturbances. The design of the proposed approach is based on type-2 fuzzy logic systems to approximate the unknown system functions present in the power system model and a robust continuous PI control to eliminate chattering phenomenon in the sliding mode control. The improvement of the robustness and the transient performance by removal of transient phase that guarantees converge in small time and eliminates the reaching phase. Moreover, PSO technique is applied to optimally select the PI sliding mode controller gains. An adaptation algorithm was derived based on the Lyapunov synthesis to provide strong robustness as well as global power system stability to cause the system follow a desired response. The performance of the proposed stabilizer is evaluated using the benchmark model of a two-area four-machine power system. Simulation results demonstrate the effectiveness and the robustness performance of the proposed approach and its ability to provide good quality of damping electromechanical oscillations while improving greatly the system stability under large operating conditions and severe faults disturbances. Furthermore, the proposed stabilizer exhibit better performance comparatively to those obtained with a conventional PSS, and with an adaptive type-2 fuzzy PSS.

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