

Adaptive Fuzzy Synergetic PSS Design to Damp Power System Oscillations

K. Mazlumi*, M. Darabian, M. Azari

Department of Electrical Engineering, University of Zanjan, Zanjan, Iran

ABSTRACT

This paper presents a novel indirect adaptive Power System Stabilizer (PSS) via a developed synergetic control methodology and fuzzy systems. Fuzzy system is utilized in an adaptive scheme to estimate the system using a nonlinear model. The synergetic control guarantees robustness of the controller and makes the controller easy to implement because of using a chatter free continuous control law. Additionally, the parameters of the controller are optimized by Imperialist Competitive Algorithm (ICA). The effectiveness of the proposed scheme is confirmed on a single machine power system while the stability is guaranteed through Lyapunov synthesis.

KEYWORDS: Imperialist Competitive Algorithm, Power System Stabilizer, Synergetic Control, Fuzzy Systems, Synchronous Machine.

1. INTRODUCTION

Electrical power systems are crucial to extend industries as well as to individuals in their day-to-day life. In order to mitigate low frequency oscillations, the generators are equipped with power system stabilizers (PSSs) that provide supplementary feedback stabilizing signals in the excitation system [1-3]. System stability may be affected by several factors, such as external disturbances or internal mechanical torques. Because of the development of the power electronics, the structural control of electric power networks has recently attracted more attention. Therefore, the flexible AC transmission system (FACTS) devices are becoming more popular. Due to the fast response of these devices, they are used to dynamically adjust the network configuration to enhance steady-state performance as well as dynamic stability [4, 5]. The availability of FACTS devices, such as thyristor controlled

series compensators (TCSCs), static var compensators (SVCs), and static synchronous series compensators (SSSCs), can provide variable turn and/or series compensation [6]. However, these devices can interfere with one another. When the controller parameters of a dynamic device are tuned to obtain the best performance, control conflicts that arise between various FACTS controllers may lead to the onset of oscillations [6, 7]. Thus, the coordinated control of these devices is very important [8]. TCSCs and SVCs have been widely studied in the technical literature and have been shown to significantly enhance system stability [9, 10]. In recent years, one of the most promising research field has been ‘‘Heuristics from Nature’’, an area utilizing analogies with nature or social systems. These techniques are finding popularity within research community as design tools and problem solvers because of their versatility and ability to optimize in complex multimodal search spaces applied to non-differentiable objective functions.

Received: 15 Jan. 2013

Accepted: 17 Mar. 2013

*Corresponding author : K. Mazlumi (E-mail: Kmazlumi@znu.ac.ir)

In recent years, some evolutionary methods such as genetic algorithm (GA) and particle swarm optimization (PSO) have been applied to the power system problems [11, 12]. As the performance of PSO is affected significantly by the selection of the control parameters, it might suffer from the problem of convergence stagnation when the optimization model is very complex. Differential evolution (DE) is a branch of evolutionary algorithms developed by Rainer Storn and Kenneth Price in 1995 [13]. It is an improved version of GA for faster optimization. DE is a population based direct search algorithm for global optimization capable of handling non-differentiable, nonlinear and multi-modal objective functions, with few, easily chosen control parameters. The major advantages of DE are its simple structure, ease of implementation and robustness. DE differs from other evolutionary algorithms (EA) in the mutation and recombination phases. DE uses weighted differences between solution vectors to change the population whereas in other stochastic techniques such as GA and Expert Systems (ES), perturbation occurs in accordance with a random quantity. DE employs a greedy selection process with inherent elitist features. Moreover, it has a minimum number of EA control parameters, which can be tuned effectively [14-15]. It has been reported in the literature that DE is far more efficient and robust compared to PSO and the EA [16].

Conventional power system stabilizers (CPSSs) are one of the premiere PSSs composed by the use of some fixed-lag-lead compensators whose parameters are calculated employing a linearized model of the power system around a given operating point and not on a wide range of operating conditions [17-20]. The configuration and parameters of power systems vary due to their nonlinear nature; consequently, they require nonlinear models as well as adaptive control schemes in a practical simulation. Therefore, an adaptive PSS, which considers the nonlinear nature of the plant and adapts its parameters to changes in the network,

is required. This issue has been posed in many papers using nonlinear approaches such as variable structure technique [21], neural network based PSS [22, 23] and fuzzy adaptive schemes [24]. The main drawbacks of these approaches are not only the parameters are not optimized but also it is difficult to implement them owing to the use of immeasurable variables in the control law [25]. Synergetic control theory has been successfully applied in the area of power electronics control. It has been applied to the control of a single boost converter in [26], and the simulations as well as the hardware characteristics have been given in [27, 28]. Furthermore, synergetic control theory has been satisfactorily applied in a practical battery charging system [29]. Synergetic control has also been developed for a single machine power system [25] in which the model all of the parameters are known and the variables are immeasurable. This makes the method to be not appropriate because of being hard to implement and the use of non-optimal controller parameters. Furthermore, in the control procedure of [25], all dynamics data of the system has been assumed to be known which is rare; mainly because of existing uncertainties and varying operating conditions. In this study, a nonlinear approach based on synergetic control theory is presented to overcome the above-mentioned problems. In this regard, a nonlinear model of the power system is used for control synthesis in an indirect adaptive approach; and the PSS parameters are optimized by an imperialist competitive technique (ICA). The proposed method is similar to sliding mode approach but without its devastating chattering drawback. Synergetic control consists mainly in forcing system trajectories to evolve on a predesigned manifold chosen by the designer accordingly to desired specifications and constraints.

2. SYNERGETIC CONTROL DESIGN PRINCIPLE

The basics of the synergetic control design procedure can be expressed as follows [25, 26]:

Consider the n^{th} order nonlinear dynamic system described by (1):

$$\dot{x} = f(x, u, t) \quad (1)$$

where, x is the state vector; u is the control input vector and f is a nonlinear function. Synthesis of a synergetic controller starts with a choice of a function of the system state variables named as the macro-variable (2):

$$\varphi = \varphi(x, t) \quad (2)$$

The control objective is to force the system to operate on the manifold $\varphi=0$. The designer can select the characteristics of the macro-variable according to the performance and control specifications (overshoot, control signal limits, etc.). Then, the desired dynamic evolution of the macro-variable can be designed imposed as:

$$T\dot{\varphi} + \varphi = 0 \quad T > 0 \quad (3)$$

T designates the designer chosen speed convergence to the desired manifold. Differentiating the macro-variable (2) along (1) leads to (4):

$$\dot{\varphi} = \frac{d\varphi}{dx} \dot{x} \quad (4)$$

Combining the equations (1), (3) and (4), equation (5) is obtained:

$$T \frac{d\varphi}{dx} f(x, u, t) + \varphi = 0 \quad (5)$$

Solving the control law, leads to (6):

$$u = u(x, \varphi(x, t), T, t) \quad (6)$$

Thus, the continuous control law, not causing chattering as in the sliding mode control approach, depends on designer chosen macro-variable and constant T ; therefore, it is imposed the desired dynamics to the system. In this process, system control design needs no model linearization and rather relies on the complete nonlinear system. The new constraint (3) as in sliding mode techniques reduces system order by one while enabling control designer to achieve global stability and parameter insensitivity. Adequate selection of the macro-variable improves the performance of the system [25]. Based on the fact that fuzzy systems are universal approximators and the work developed in [30, 31], an indirect fuzzy synergetic controller is proposed in this paper.

3. FUZZY BASIC FUNCTIONS

The basic configuration of fuzzy logic systems [17] consists of a collection of fuzzy IF-THEN rules:

$$R(1) : \text{IF } x_1 \text{ is } F_1^l \text{ and } \dots \text{ and } x_n \text{ is } F_n^l \text{ THEN } y \text{ is } G^l. \quad (7)$$

The fuzzy logic system performs a mapping from $U = U_1 \times \dots \times U_n \subset R^n$ to R .

where $x = (x_1, \dots, x_n)^T \in U$ and $y \in R$ represent input and output of the fuzzy logic system, respectively. F_i^l and G^l are labels of fuzzy sets in U_i and R , respectively, where $l = 1, 2, \dots, M$. Each fuzzy IF-THEN rule of (7) defines a fuzzy implication, $F_1^l \times \dots \times F_n^l \rightarrow G^l$, which is a fuzzy set defined in the product space $U \times R$.

Using singleton fuzzification, product inference, and center-average defuzzification, the output of the fuzzy system is obtained as [30,31]:

$$y(x) = \frac{\sum_{l=1}^M y^l (\prod_{i=1}^n \mu_{F_i^l}(x_i))}{\sum_{l=1}^M (\prod_{i=1}^n \mu_{F_i^l}(x_i))} \quad (8)$$

where, $\mu_{F_i^l}$ represents the membership function of the linguistic variable x_i ; and y^l shows the point in R at which μ_{G^l} achieves its maximum value (assuming $\mu_{G^l}(y^l) = 1$).

By introducing the concept of the fuzzy basis function vector $\xi(x)$, equation (8) can be rewritten as:

$$y(x) = \theta^T \xi(x) \quad (9)$$

where, $\theta_l = [\theta_1 \dots \theta_M]^T$ and $\xi(x) = [\xi^1(x) \dots \xi^M(x)]$; and the fuzzy basis functions is defined as:

$$\xi_1(x) = \frac{\prod_{i=1}^n \mu_{F_i^1}(x_i)}{\sum_{l=1}^M (\prod_{i=1}^n \mu_{F_i^l}(x_i))} \quad (10)$$

4. IMPERIALIST COMPETITIVE ALGORITHM

The ICA was first proposed in [32]. It is inspired from the imperialist competition. It starts with an initial population called colonies. The colonies are then categorized into two groups, namely, imperialists (best solutions) and colonies (rest of the solutions). The imperialists try to absorb more colonies to their

empire [33]. The colonies will change according to the policies of imperialists. The colonies may take the place of their imperialist if they become stronger than they do (propose a better solution). The flowchart of the IC algorithm is shown in Fig. 1. The steps of the ICA are described as follows:

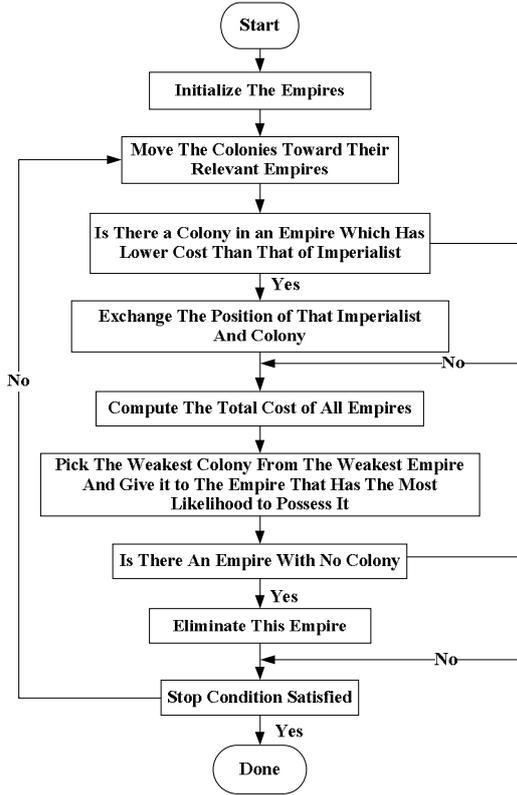


Fig. 1. ICA flowchart

Step 1. Generate an initial set of colonies with a size of N_c .

Step 2. Set iteration=1.

Step 3. Calculate the objective function for each colony and set the power of each colony as follows:

$$CP_c = OF \quad (11)$$

Step 4. Keep the best N_{imp} colonies as the imperialists and set the power of each imperialist as follows:

$$IP_i = OF \quad (12)$$

Step 5. Assign the colonies to each imperialist based the calculated IP_i . This means the number of colonies owned by each

$$\text{imperialist} \propto \left(\frac{IP_i}{\sum_{j=1}^{N_{imp}} IP_j} \right) \times (N_c - N_{imp})$$

is proportional to its power IP_i .

Step 6. Move the colonies towards their relevant imperialist using crossover and mutation operators.

Step 7. Exchange the position of a colony and the imperialist if it is stronger $CP_c > IP_i$.

Step 8. Compute the empire's power, that is, EP_i for all empires as follows:

$$EP_i = \frac{1}{N_{E_i}} \times (\chi_1 \times IP_i + \chi_2 \times \sum_{c \in E_i} CP_c) \quad (13)$$

where, χ_1 and χ_2 are weighting factors that are adaptively selected.

Step 9. Pick the weakest colony and give it to one of the best empires (select the destination empire probabilistically based on its power, EP_i).

Step 10. Eliminate the empire that has no colony.

Step 11. If more than one empire remained, then return to Step 6.

Step 12. End.

The development of an indirect adaptive fuzzy synergetic PSS will now be introduced followed by simulations results.

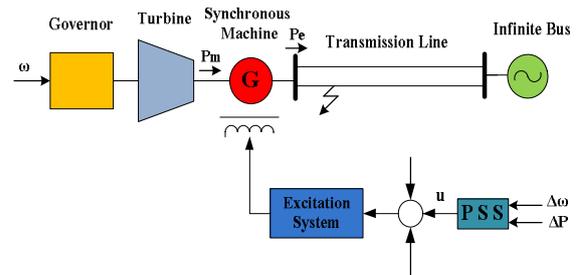


Fig. 2. Single machine infinite-bus power system

5. INDIRECT ADAPTIVE FUZZY SYNERGETIC CONTROLLER

The design of an indirect fuzzy synergetic controller is illustrated in this section. In order to evaluate the validity of the proposed approach, an adaptive fuzzy synergetic power system stabilizer (AFSPSS) is applied to a perturbed power system consisting of a synchronous machine connected to an infinite bus through a parallel transmission line with the

AFSPSS output being fed to the exciter voltage summing junction. The diagram of this power system is depicted in Fig. 2. The major aim of PSS is to damp the power system oscillations which occur under any disturbances such as sudden change of the loads or in the event of a short-circuit occurrence. Power flow is drastically prevented by these oscillations and they may lead inability to provide power demand or even loss of synchronism that may eventually lead, in the worst case, to blackouts. The dynamic model of the power system is provided in detail in Appendix A.

By a set of nonlinear differential equations, a power system can be modeled as follow [34, 35]:

$$\dot{x}_1 = \alpha x_2 \quad (14)$$

$$\dot{x}_2 = f(x_1, x_2) + g(x_1, x_2)u$$

where, $x_1 = \Delta\omega$ is speed deviation; $x_2 = P_e - P_m$ is accelerating power system; $\alpha = -1/(2H)$ in which H is machine inertia constant in per-unit; $x = [x_1, x_2]^T \in R^2$ is a measurable system state vector and u is the necessary control signal to be designed, *i.e.* the PSS output; $f(x)$ and $g(x)$ are nonlinear functions and we have $g(x) \neq 0$ in the controllability region. The synergetic synthesis of the power system stabilizer starts by defining a macro-variable given in (15):

$$\varphi = k_1 x_1 + x_2 \quad (15)$$

$$\dot{\varphi} = K^T x + f(x_1, x_2) + g(x_1, x_2)u \quad (16)$$

Without loss of generality, let choose $K^T = [0 \ \alpha k_1]$ in which k_1 is a designer chosen constant. Combining Equations (16) and (5) yields:

$$f(x_1, x_2) + g(x_1, x_2)u = -\frac{1}{T}\varphi - K^T x \quad (17)$$

The synergetic control law is then obtained and is given by (18):

$$u = \frac{1}{g(x_1, x_2)}(-f(x_1, x_2) - \frac{1}{T}\varphi - K^T x) \quad (18)$$

In the more realistic case where f and g are unknown, they are replaced by their fuzzy estimates $\hat{f}(x/\theta_f) = \theta_f^T \zeta(x)$ and $\hat{g}(x/\theta_g) = \theta_g^T \xi(x)$. It is to be noted that the approximation error issue has been addressed in great details in [30, 36] where the Stone-Weierstrass theorem is used to prove that fuzzy systems can approximate any

continuous real function on a compact set to any arbitrary accuracy while fuzzy rules are derived based on experts' recommendations.

Thus, the new control law is rewritten as:

$$u_c = \frac{1}{\hat{g}(x/\theta_g)}(-\hat{f}(x/\theta_f) - \frac{1}{T}\varphi - K^T x) \quad (19)$$

Theorem: Consider the control problem of the nonlinear system (13), using control action u_c (18), and using \hat{f} and \hat{g} while parameter vectors θ_f and θ_g are adjusted through the adaptive laws $\dot{\theta}_f = r_1 \varphi \zeta(x)$ and $\dot{\theta}_g = r_2 \varphi \xi(x) u_c$, the closed loop system signals will be bounded and the tracking error will converge to zero asymptotically.

Proof. Define the optimal parameters of fuzzy systems:

$$\hat{\theta}_f = \arg \min_{\theta_f \in Z_f} [\sup_{x \in R^n} |\hat{f}(\frac{x}{\theta_f}) - f(x)|] \quad (20)$$

$$\hat{\theta}_g = \arg \min_{\theta_g \in Z_g} [\sup_{x \in R^n} |\hat{g}(\frac{x}{\theta_g}) - f(x)|] \quad (21)$$

Where, Z_f and Z_g are constraint sets for θ_f and θ_g , respectively.

Define the minimum approximation error by:

$$\varepsilon = f(x_1, x_2) - \hat{f}(x/\theta_f) + (g(x_1, x_2) - \hat{g}(\frac{x}{\theta_g}))u_c \quad (22)$$

Then, we have:

$$\begin{aligned} \dot{\varphi} &= K^T x + f(x_1, x_2) + g(x_1, x_2)u_c - \hat{g}(\frac{x}{\theta_f})u_c - \hat{g}(\frac{x}{\theta_g})u_c \\ &= \varepsilon + (\hat{\theta}_f^T - \theta_f^T)\xi(x) + (\hat{\theta}_g^T - \theta_g^T)\xi(x) - \frac{1}{T}\varphi \end{aligned} \quad (23)$$

Let $\phi_f = (\hat{\theta}_f - \theta_f)$ and $\phi_g = (\hat{\theta}_g - \theta_g)$

Therefore, we may rewrite (23) as:

$$\dot{\varphi} = \phi_f^T \xi(x) + \phi_g^T \xi(x)u_c - \frac{1}{T}\varphi + \varepsilon \quad (24)$$

Now consider the Lyapunov function candidate:

$$V = \frac{1}{2}(\varphi^2 + \frac{1}{r_1}\phi_f^T \phi_f + \frac{1}{r_2}\phi_g^T \phi_g) \quad (25)$$

where, r_1 and r_2 are positive constants [35] that will be used as learning rates in the adaptive procedure. Time derivative of V is obtained as:

$$\begin{aligned} \dot{V} = & \varphi \dot{\varphi} + \frac{1}{r_1} \phi_f^T \dot{\phi}_f + \frac{1}{r_2} \phi_g^T \dot{\phi}_g = \varphi(\phi_f^T \zeta(x) + \phi_f^T \zeta(x) u_c \\ & - \frac{1}{T} \varphi + \varepsilon) + \frac{1}{r_1} \phi_f^T \dot{\phi}_f + \frac{1}{r_2} \phi_g^T \dot{\phi}_g \leq \frac{1}{r_1} \phi_f^T (r_1 \varphi \zeta(x) + \dot{\phi}_f) \\ & + \frac{1}{r_2} \phi_g^T (r_2 \varphi \zeta(x) u_c + \dot{\phi}_g) + \varphi \varepsilon - \frac{1}{T} |\varphi| \end{aligned} \quad (26)$$

where, $\dot{\phi}_f = -\dot{\theta}_f$ and $\dot{\phi}_g = -\dot{\theta}_g$. Substituting $\dot{\theta}_f$ and $\dot{\theta}_g$ into (26), leads to:

$$\dot{V} \leq \varphi \varepsilon - \frac{1}{T} |\varphi| \quad (27)$$

Based on the universal approximation theorem $\varphi \varepsilon$ is very small, and thus we have:

$$\dot{V} \leq 0.$$

6. SIMULATION RESULTS

In order to assess the performance of the proposed stabilizer, a three phase to ground short-circuit is simulated for different operating points in a single machine power system. In (28), a conventional power system stabilizer is used for comparison [2, 22]. Then, the simulation results are discussed for different operating conditions.

$$u_{pss} = \frac{K_S(1+sT_1)(1+sT_3)}{(1+sT_w)(1+sT_2)(1+sT_4)} \quad (28)$$

A performance index can be defined by the Integral of Time multiply Absolute Error (ITAE) of the speed deviations of machines. Accordingly, the objective function (OF) is set to be:

$$OF = \int_{t=0}^{t=t_1} t |\Delta\omega(t)| dt \quad (29)$$

where, t_1 is the time range of the simulation and $\Delta\omega(t)$ is the system speed variation.

The IC algorithm has some abilities such as the faster convergence and less time consuming, the ability to jump out the local optima, providing the correct results with high accuracy in the initial iterations, superiority in computational simplicity, success rate and solution quality that leads to its supremacy over other evolutionary algorithms like genetic algorithm, PSO. Hence, in this study an ICA technique is employed to optimally tune the proposed power system stabilizer. The aim of

the optimization is to search for the optimum controller parameters setting that reflect the settling time and overshoots of the system. On the other hand, the goals are improving the damping characteristics as well as obtaining a good performance under all operating conditions and various loads and finally designing a low order controller for easy implementation. Synergetic control parameters influence has been partially evaluated in [27-39] using only different values for T and k_I while a systematic optimization of these parameters is carried out in this paper.

The results of the proposed controller parameters values obtained by the time domain objective function through ICA are tabulated in Table 1. Also, the variations of the objective function are illustrated in Fig. 3. The validity of the proposed approach under severe disturbance is verified by applying a three-phase fault. The fault duration is 6 cycles and occurs at 0.1 s. The Performance of a classic power system stabilizer (CPSS), an adaptive fuzzy synergetic PSS (AFSPSS) and without PSS (WPSS) are demonstrated in the next sections which clearly indicate the superiority of the proposed AFSPSS controller owing to the rapid mitigation of oscillations in both speed deviation and active power responses.

Table 1. The optimized parameters

	T	K _I
Initial value	Random value	Random value
Final value	0.38	-3.75

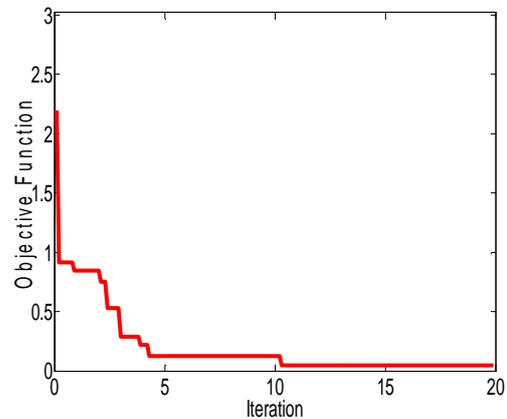


Fig. 3. Variations of the objective function

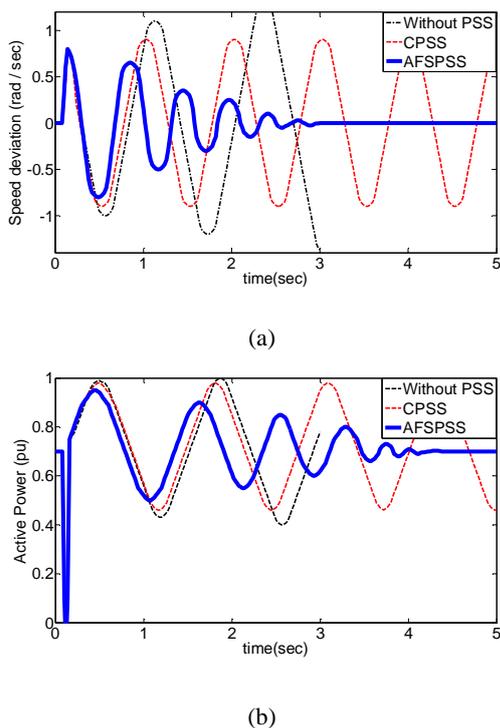


Fig. 4. Response for case 1: (a) rotor speed deviation; (b) active electrical power

6.1. Case 1

Heavy loading conditions can be considered with $P_e=0.7$ pu and $Q_e=0.8$ pu. The variations of the active power of a selected line and rotor speed deviation of a generator located close to the fault position are plotted against time for the faulty operating condition as shown in Fig. 4. According to Fig. 4.a, it is evident that the peak of the speed deviation for the proposed method is 0.79 which occurs at $t=0.16$ s; it is gradually decreased and finally eliminated at $t=2.91$ s; whereas for CPSS, the peak of these oscillations is 0.88 and is fully damped after $t=5$ s. Furthermore, these oscillations are too much in the case of WPSS in which the system is no longer stabilized. Similar results can be observed in the Fig. 4.b. In addition, the settling time of the oscillations is $t=4.27$ s for the proposed controller. Therefore, the system response in the absence of PSS presents dangerous oscillations that would end up with loss of synchronism. In addition, the proposed AFSPSS controller achieves robust performance and provides superior damping in

comparison with CPSS and WPSS, and consequently enables better power flow.

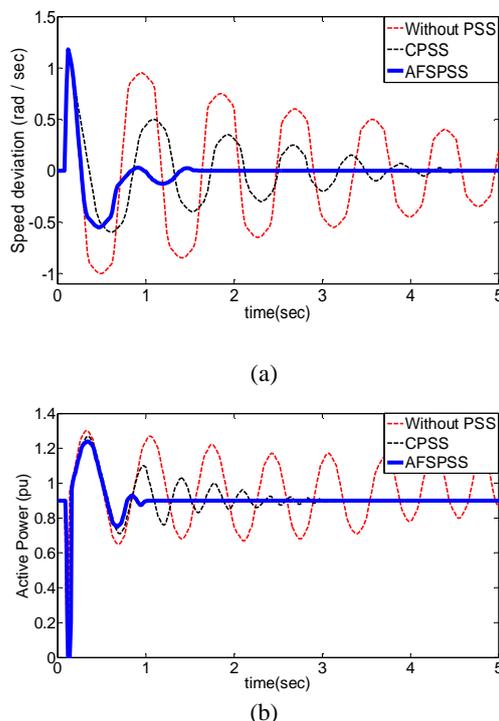


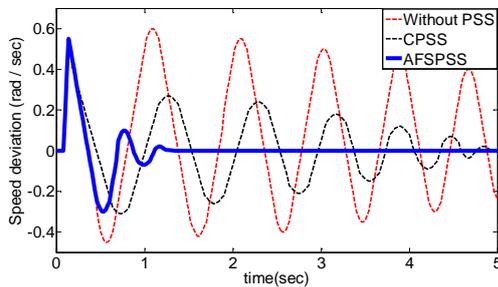
Fig. 5. Response for case 2: (a) rotor speed deviation; (b) active electrical power

6.2. Case 2

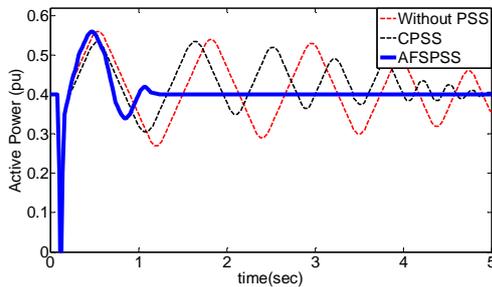
In leading power factor operating point, the synchronous machine absorbs the reactive power. In this case, P_e and Q_e are considered to be 0.9 and -0.3 pu, respectively. The response of this operating condition is depicted in Fig. 5. According to Fig. 5.a, it is clear that the peak of speed deviation for the proposed method is 1.18 which occurs at $t=0.16$ s; it is gradually decreased and finally eliminated at $t=1.58$ s; whereas for CPSS, the peak of the oscillations is 1.11 and is fully damped at $t=4.58$ s. Furthermore, this value is 1.58 for WPSS and is eliminated after $t=5$ s. As seen in Fig. 5.b, the settling time of oscillation is $t=1.02$ and 3.17 s for the proposed controller and CPSS, respectively. Hence, the response of the proposed AFSPSS controller shows good damping characteristics of the low frequency oscillations in comparison with the CPSS in the speed deviation and active power.

6.3. Case 3

Light loading conditions can be considered with $P_e=0.4$ pu and $Q_e=0.2$ pu. Figure 6 shows the response to same disturbance for normal loading condition. As seen in Fig. 6.a, the settling time of these oscillations is approximately 1.32 s with the proposed controller and 4.96 s for the CPSS. Therefore, the designed controller is capable of providing sufficient damping to the system oscillatory modes.



(a)



(b)

Fig. 6. Response for case 3: (a) rotor speed deviation; (b) active electrical power

According to Fig. 6.b, the peak of the active power for the proposed controller is 0.56 which occurs at $t=0.16$ s; it is gradually decreased and finally settled at $t=1.22$ s. Whereas for CPSS, the settling time is 4.98 s. As a result, the proposed AFSPSS achieves good damping features as well as rapid suppression of power system oscillations.

7. CONCLUSIONS

This paper focused on the development of a new adaptive power system stabilizer using the

both synergetic control and fuzzy systems and stability thereof is guaranteed by Lyapunov synthesis. The major advantage of the proposed approach arises from the fact that the presented power system stabilizer does not require to use of non-measurable variables, and consequently is easy to implement. Additionally, an ICA technique has been employed to obtain the optimum values of the PSS parameters. The validity of the proposed approach has been tested on a single machine infinite bus power system. Simulation results assure the effectiveness of the proposed controller using a full nonlinear system model in providing better damping characteristic to the system oscillations over a wide range of loading conditions. In addition, unlike adaptive fuzzy sliding mode schemes, the proposed approach does not suffer from chattering for the control law.

APPENDIX A

The dynamic model of power systems is written as follows:

- Mechanical dynamics of the generator:

$$\frac{d\delta}{dt} = 2\pi f_0 (\omega - 1) \quad (A.1)$$

$$\frac{d\omega}{dt} = \frac{1}{2H} [p_m - p_e - D(\omega - 1)] \quad (A.2)$$

where, δ is the rotor angle of the generator; f_0 is the power system synchronous frequency; ω is the rotor angular speed of the generator; H is the inertial constant; P_m is the mechanical power input to the generator shaft; P_e is the active electrical power delivered by the generator; D is the mechanical damping coefficient of the generator.

The input mechanical power P_m is treated as a constant in the excitation controller design, *i.e.*, it is assumed that the governor action is slow enough not to have any significant impact on the machine dynamics.

- Electrical dynamics of the generator:

$$\frac{dE_q}{dt} = \frac{1}{T_{do}} [k_e u_{PSS} - E_q - I_d (X_d - X'_d)] \quad (A.3)$$

The definitions of the symbols are as follows: E'_q is the transient electro-motive force (EMF) in the quadratic axis of the generator; T'_{do} is the direct-axis open-circuit transient time constant; K_e is the gain of the exciter; I_d is the direct- and quadrature-axis components of the generator armature current; X_d is the direct-axis and quadrature-axis components of the generator synchronous reactance; X'_d is the direct-axis component of the transient reactance of the generator.

It is assumed that the outputs of the PSS can be applied instantly to the output of the exciter when considering the PSS design. This assumption can be justified by the fact that the voltage control system (including the PSS and exciter) is very fast in comparison to the dynamics of the rest of the system; *i.e.*, the time constant of the fast-acting excitation system is far lower than that of the rest of the system. This assumption implies that the design of the nonlinear PSS can only consider the dynamics of the synchronous generator.

• Electrical equations

$$P_e = \frac{E'_q}{X_{d\Sigma}} \sin \delta, \quad I_d = \frac{E'_q - V \cos \delta}{X_{d\Sigma}}, \quad I_q = \frac{V \sin \delta}{X'_{d\Sigma}}$$

$$V_d = -X_q I_q, \quad V_q = E'_q - X'_q I_q, \quad V_t = \sqrt{V_d^2 + V_q^2}$$

$$X'_{d\Sigma} = X'_d + X_T + X_L$$

APPENDIX B

The parameters of the synchronous machine, excitation system and conventional PSS are given in Table 2:

Table 2. System parameters used in the simulation process

Parameters	Value	Parameters	Value
X_d	2.19	X_L	0.1
X_q	1.01	X_T	0.1
X'_d	0.18	K_e	1
X'_q	0.2	K_s	6.894
T'_{do}	4.14	T_1	0.01721
H	6	T_2	0.0722
f_0	50	T_3	0.0126
D	5	T_4	0.0619
P_m	1	T_w	10

REFERENCES

[1] P.M. Anderson and A.A. Fouad, *Power system control and stability*, IEEE Press, New York, 1993.

[2] P. Kundur, *Power system control and stability*, McGraw-Hill Inc, 1994.

[3] H. Shayeghi, A. Safari and H.A. Shayanfar, "PSS and TCSC damping controller coordinated design using PSO in multi-machine power system," *Energy Conversion and Management*, vol. 51, no. 12, pp. 2930-7, 2010.

[4] J.J. Sanchez-Gasca, "Coordinated control of two FACTS devices for damping inter area oscillations," *IEEE Transactions on Power Systems*, vol. 13, no. 2, pp. 428-434, May 1997.

[5] R. Mohan. Mathur and R.K. Varma, *Thyristor-based FACTS controller for electrical transmission system*, IEEE Press/Wiley Inter science, 2002.

[6] K. Clark, B. Fradanesh and R. Adapa, "Thyristor-controlled series compensation application study- Control interaction considerations," *IEEE Transactions on Power Delivery*, vol. 10, no. 2, pp. 1031-1037, 1995.

[7] D.P. He, C.Y. Chung and Y. Xue, "An eigenstructure-based performance index and its application to control design for damping inter-area oscillations in power systems," *IEEE Transactions on Power Systems*, vol. 26, no. 4, pp. 2371-2380, 2011.

[8] Y.C. Chang, R.F. Chang, T.Y. Hsiao and C.N. Lu, "Transmission system load ability enhancement study by ordinal optimization method," *IEEE Transactions on Power Systems*, vol. 26, no. 1, pp. 451-459, 2011.

[9] X. Lei, E.N. Lerch and D. Povh, "Optimization and coordination of damping controls for improving system dynamic performance," *IEEE Transactions on Power Systems*, vol. 16, no. 3, pp. 473-480, 2001.

[10] N. Mithulananthan, C.A. Canizares, J. Reeve, and G.J. Rogers, "Comparison of PSS, SVC, and STATCOM controllers for damping power system oscillations," *IEEE Transactions on Power Systems*, vol. 18, no. 2, pp. 786-792, 2003.

[11] S. Panda and N.P. Padhy, "Comparison of particle swarm optimization and genetic algorithm for FACTS-based controller design,"

- Applied Soft Computing*, vol. 8, no. 4, pp. 1418–1427, 2008.
- [12] P. Bhatt, R. Roy and S.P. Ghoshal, “GA/particle swarm intelligence based optimization of two specific varieties of controller devices applied to two-area multi-units automatic generation control,” *International Journal of Electrical Power and Energy Systems*, vol. 32, pp. 299-310, 2010.
- [13] R. Stron and K. Price, “Differential evolution – a simple and efficient adaptive scheme for global optimization over continuous spaces,” *Journal of Global Optimization*, vol. 11, pp. 341-59, 1997.
- [14] R. Gamperle, S.D. Muller and P. Koumoutsakos, “A parameter study for differential evolution,” *Proc. of the WSEAS International Conference on Advance Intelligent Fuzzy System and Evolutionary Computing*, pp. 293-298, 2002.
- [15] D. Zaharie, “Critical values for the control parameters of differential evolution algorithms,” *Proc. of the 8th International Conference on Soft Computing*, pp. 62-67, 2002.
- [16] J. Vesterstrom and R. Thomsen, “A comparative study of differential evolution, particle swarm optimization, and evolutionary algorithms on numerical benchmark problems,” *Proc. of the IEEE congress on Evolutes Compute*, vol. 2, 2004.
- [17] F.P. Demello and C. Concordia, “Concept of synchronous machine stability as affected by excitation control,” *IEEE Transactions on Power Apparatus Systems*, vol. 88, no. 4, pp. 316-329, 1996.
- [18] H. Vu and J.C. Agee, “Comparison of power system stabilizers for damping local mode oscillations,” *IEEE Transactions on Energy Conversion*, vol. 8, no. 3, pp. 533-539, 1993.
- [19] J.A. Simoes, F.D. Freitas and H.E. Pena, “Power system stabilizer design via structurally constrained optimal control,” *International Journal of Electrical Power and Energy Systems*, vol. 33, no. 1, pp. 33-40, 1995.
- [20] R. Gupta, B. Bandyopadhyay and A.M. Kulkarni, “Design of power system stabilizer for single machine system using robust fast output sampling feedback technique,” *Electric Power Systems Research*, vol. 65, no. 3, pp. 247-257, 2003.
- [21] Y. Cao, L. Jiang, S. Cheng, D. Chen, O.P. Malik and G.S. Hope, “A nonlinear variable structure stabilizer for power system stability,” *IEEE Transactions on Energy Conversion*, vol. 9, pp. 489-495, 1994.
- [22] N. Hosseinzadeh and A. Kalam, “A rule-based fuzzy power system stabilizer tuned by a neural network,” *IEEE Transactions on Energy Conversion*, vol. 14, pp.773-779, 1999.
- [23] R. Segal, M.L. Kothari and S. Madnani, “Radial basis function (RBF) network adaptive power system stabilizer,” *IEEE Transactions on Power Systems*, vol. 15, pp. 722-727, 2000.
- [24] T. Hussein, M.S. Saad, A.L. Elshafei and A. Bahgat, “Robust adaptive fuzzy logic power system stabilizer,” *Expert Systems with Applications*, vol. 36, pp. 12104-12, 2009.
- [25] Z. Jiang, “Design of a nonlinear power system stabilizer using synergetic control theory,” *Electric Power Systems Research*, vol. 79, no. 6, pp. 855-862, 2009.
- [26] A. Kolesnikov, G. Veselov, A. Monti, F. Ponci, E. Santi and R. Dougal, “Synergetic synthesis of DC–DC boost converter controllers: theory and experimental analysis,” *Proc. of the 17th Applied Power Electronics Conference and Exposition*, vol. 1, pp. 409-415, 2002.
- [27] E. Santi, A. Monti, Li. Donghong, K. Proddutur and R.A. Dougal, “Synergetic control for DC–DC boost converter: implementation options,” *IEEE Transactions on Industrial Application*, vol. 39, no. 6, pp. 1803-13, 2003.
- [28] I. Kondratiev, E. Santi, R. Dougal and G. Veselov, “Synergetic control for m-parallel connected DC–DC buck converters,” *Proc. of the 30th Annual PES Conference*, vol. 1, pp. 182-188, 2004.
- [29] Z. Jiang and R.A. Dougal, “Synergetic control of power converters for pulse current charging of advanced batteries from a fuel cell power source,” *IEEE Transactions on Power Electronics*, vol. 19, no. 4, pp. 1140-1150, 2004.
- [30] L.X. Wang, “Stable adaptive fuzzy control of nonlinear systems,” *IEEE Transaction on Fuzzy System*. vol. 1, no. 2, pp. 146-155, 1993.
- [31] J. M. Mendel, “Fuzzy logic systems for engineering: a tutorial,” *Proc. of the IEEE Browse Journals & Magazines*, vol. 83, no. 3, pp. 345-377, 1995.
- [32] J. Atashpaz-Gargari and E. Lucas, “Imperialist

- competitive algorithm: an algorithm for optimization inspired by imperialistic competition,” *Proc. of the IEEE Congress on Evolutionary Computation*, pp. 4661-7, 2007.
- [33] S. Jalilzadeh and M. Azari, “A novel approach for PID designing for load frequency control system,” *International Review on Modeling and Simulation*, vol. 5, no. 3, pp. 1159-64, 2012.
- [34] N. Hosseinzadeh and A. Kalam, “An indirect adaptive fuzzy logic power system stabilizer,” *International Journal of Electrical Power and Energy Systems*, vol. 24, no. 10, pp. 837-842, 2002.
- [35] A. Elshafei and K. El-Metwally, “Power system stabilization via adaptive fuzzy-logic control,” *Proc. of the 12th IEEE International Symposium on Intelligent Control*, 1997.
- [36] B. Kosko, “Fuzzy systems are universal approximators,” *Proc. of the IEEE International Conference on Fuzzy Systems*, pp. 1143-1162, 1992.
- [37] S.H. Nusawardhana, S.H. Zak and W.A. Crossley, “Nonlinear synergetic optimal controllers,” *Journal of Guidance, Control and Dynamics*, vol. 30, no. 4, 2007.
- [38] I. Kondratiev and R. Dougal, “Current distribution control design for paralleled DC/DC converters using synergetic control theory,” *Proc. of the IEEE Power Electronics Specialists Conference*, 2007.
- [39] E. Santi, A. Monti, D. Li, K. Proddatur and R.A. Dougal, “Synergetic control for power electronics applications: a comparison with the sliding mode approach,” *Journal of Circuits, Systems and Computers*, vol. 13, no. 4, pp. 737-760, 2004.