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Research Article

Fuzzy Sliding Mode Control Design and Particle Swarm Optimization Based PSS for Multimachine Power System

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Abstract: The aim of this study is to design nonlinear robust controllers for multimachine power systems. A technique for the optimal tuning of Power System Stabilizer (PSS) by integrating the Particle Swarm Optimization (PSO) combined with the Fuzzy Sliding Mode Control (FSMC) is proposed in this study. The fuzzy tuning schemes are employed to improve control performance and to reduce chattering in the sliding mode. The objective of this method is to enhance the stability and the dynamic response of the multimachine power system operating in different operating conditions. In order to test the effectiveness of the proposed method, the simulation results show the damping of the oscillations of the angle and angular speed with reduced overshoots and quick settling time.

Keywords: Fuzzy logic, multimachine power system, particle swarm optimization algorithm, power system stabilizer, sliding mode control, stability

INTRODUCTION

Stability of power systems is one of the most important aspects in electric system operation. The size and complexity of modern electric power systems necessitates the construction of reduced-order dynamic models, or dynamic equivalents (Amin and Hemmati, 2012). Determination of transient stability is one of the major items of power system operation and planning (Mendiratta and Jayapal, 2010).

Most controllers PSSs used in electric power systems employ the linear control theory approach based on a linear model of a fixed configuration of the power system and thus tuned at a certain operating condition. The fixed parameter PSS, called conventional PSS, is widely used in power systems, it often does not provide satisfactory results over a wide range of operating conditions (Ben-Meziane *et al*., 2013) Overcome these drawbacks, a lot of different techniques have been reported in the literature pertaining to coordinated design problem of the PSS (Abido, 2010).

A Power System Stabilizer based on Particle Swarm Optimization (PSO) is proposed in this study. PSO technique is used for optimal tuning of PSS parameter to reduce the convergence time. Unlike the other heuristic techniques, it has a flexible and well-balanced mechanism to enhance the global and local exploration abilities. Also, it suffices to specify the objective function and to place finite bounds on the optimized Parameters (Shayeghi *et al*., 2008).

The Sliding Mode Control (SMC) is essentially a switching feedback control where the gains in each feedback path switch between two values according to some rule. The switching feedback law drives the controlled system's state trajectory in to specified surface called the sliding surface which represents the desired dynamic behavior of the controlled system (Al-Duwaish and Al-Hamouz, 2011). The SMC has been reported as one of the most effective control methodologies for nonlinear power system applications due to its disturbance rejection, strong robustness subject to system parameter variations, uncertainties and external disturbances (Al-Duwaish and Al-Hamouz, 2011). The control gain of sliding mode may be selected high value, which causes the chattering on the sliding surface, or, this gain may be chosen smaller, which cause increasing of tracking error (Ha *et al*., 2001). Using Mamdani fuzzy inference method to adjust the corrective gain in sliding mode control. The fuzzy logic is used to overcome the disadvantages of the sliding mode control, while the FSMC provides better damping and reduced chattering. The effectiveness of the proposed method is tested on a multimachine power system under different operating conditions. The results evaluations show that the proposed method achieves good robust performance for damping low frequency oscillations under different operating conditions.

Multimachine power system model: Under some standard assumptions, the dynamics of n interconnected

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generators through a transmission network can be described by classical model with flux decay dynamics. The network has been reduced to internal bus representation assuming loads to be constant impedances and considering the presence of transfer conductance. The dynamical model of the ith machine is represented by the classical third order model (Colbia-Vegaa *et al*., 2008):

$$\begin{aligned}\dot{\delta}_i &= \omega_i - \omega_s \\ \dot{\omega}_i &= \frac{\omega_s}{2H_i}\left(Pm_i - D_i\left(\omega_i - \omega_s\right) - E'_{qi}I_{qi}\right) \\ \dot{E}'_{qi} &= \frac{1}{T'_{di}}\left(E_{fi} - E'_{qi} - \left(X_{di} - X'_{di}\right)I_{di}\right)\end{aligned} \tag{1}$$

I_{qi} and I_{di} represent currents in d-q reference frame of the ith generator, E'_{qi} is the transient EMF in the quadrature axis, E_{fi} (t) is the equivalent EMF in the excitation coil, X_{di} and X'_{di} are direct axis reactance and direct axis transient reactance, respectively:

$$\begin{cases} I_{qi} = G_{ii}E'_{qi} + \sum\limits_{j=1, j\neq i}^{n} E'_{qi}\left\{G_{ij}\cos\left(\delta_j - \delta_i\right) - B_{ij}\sin\left(\delta_j - \delta_i\right)\right\} \\ I_{di} = -B_{ii}E'_{qi} - \sum\limits_{j=1, j\neq i}^{n} E'_{qi}\left\{G_{ij}\sin\left(\delta_j - \delta_i\right) + B_{ij}\cos\left(\delta_j - \delta_i\right)\right\} \end{cases} \tag{2}$$

where, Pm_i is the mechanical input power assumed to be constant, D_i is the damping factor; all parameters are in p.u., H_i is the inertia constant, in seconds, T'_{di} is the direct axis transient short circuit time constant, in seconds, δ_i is the rotor angle, in radians, ω_i is the relative speed, $\omega_s = 2\pi f$ is the synchronous machine speed, in rad/sec and G_{ij}, B_{ij} is the ith row and jth column element of the nodal conductance matrix and nodal susceptance matrix respectively, which are symmetric, at the internal nodes after eliminating all physical buses in p.u. We consider E_{fi} (t) as the input of the system (Colbia-Vegaa *et al*., 2008). The state representation of the ith machine of a multimachine power system can be written in the following form:

$$x_i = \left[x_{i1}, x_{i2}, x_{i3}\right]^T = \left[\delta_i, \omega_i, E'_{qi}\right]$$

For i = 1, 2, .., n, represents the state vector of ith subsystem and the control applied is given by:

$$u_i = \frac{1}{T'_{di}}E_{fi} \tag{3}$$

$$\begin{aligned}\dot{x}_{i1} &= x_{i2} \\ \dot{x}_{i2} &= f_{i1}(X) \\ \dot{x}_{i3} &= f_{i2}(X) + u_i\end{aligned} \tag{4}$$

where,

$$\begin{cases} f_{i1}(X) = a_i - b_i x_{i2} - c_i x_{i3}^2 - d_i x_{i3}\sum\limits_{j=1, j\neq i}^{n} x_{j3}\left\{G_{ij}\cos\left(x_{j1} - x_{i1}\right) - B_{ij}\sin\left(x_{j1} - x_{i1}\right)\right\} \\ f_{i2}(X) = -e_i x_{i3} + h_i\sum\limits_{j=1, j\neq i}^{n} x_{j3}\left\{G_{ij}\sin\left(x_{j1} - x_{i1}\right) + B_{ij}\cos\left(x_{j1} - x_{i1}\right)\right\} \end{cases} \tag{5}$$

and,

$$a_i = \frac{\omega_s}{2H_i}Pm_i \;;\; \mathrm{b}_i = \frac{\omega_s}{2H_i}\mathrm{D}_i \;;\; \mathrm{c}_i = \frac{\omega_s}{2H_i}G_{ii}$$

$$\mathrm{d}_i = \frac{\omega_s}{2H_{i\,i}} \;;\; e_i = \frac{\left(1 - \left(X_{di} - X'_{di}\right)B_{ii}\right)}{T'_{di}} ;\; \mathrm{h}_i = \frac{X_{di} - X'_{di}}{T'_{di}}$$

PARTICLE SWARM OPTIMIZATION BASED ON PSS DESIGN

The PSO method is a member of wide category of Swarm Intelligence methods for solving the optimization problems (Sidhartha and Ardil, 2008). It employs an appropriate model of fitness for particle, to evaluate fitness value of each particle and to record the particle that is the highest fitness value in an iterative procedure (Liang *et al*., 2011). The position corresponding to the best fitness is known as pbest and the overall best out of all the particles in the population is called gbest (Sidhartha and Ardil, 2008). The modified velocity and position of each particle can be calculated using the current velocity and the distance from the pbest$_{j,g}$ to gbest$_g$ as shown in the following formulas (Gaing, 2004):

$$v_{j,g}^{(t+1)} = w\, v_{j,g}^{(t)} + c_1 r_1\left(pbest_{j,g} - x_{j,g}^{(t)}\right) + c_2 r_2\left(gbest_g - x_{j,g}^{(t)}\right) \tag{6}$$

$$x_{j,g}^{(t+1)} = x_{j,g}^{(t)} + v_{j,g}^{(t+1)} \quad ; \; j = 1, 2, ..., n \text{ and } g = 1, 2, ..., m \tag{7}$$

where, n is the number of particles in a group, m is the number of members in a particle, t is pointer of iterations (generations), v is the velocity, x is the position of each particle, c_1, c_2 are positive constants referred to as acceleration constants and must be $c_1 + c_2 \leq 4$, usually $c_1 = c_2 = 2$, r_1, r_2 are random numbers between 0 and 1 and w is the inertia weight, which produces a balance between global and local explorations requiring less iteration on average to find a suitably optimal solution. It is determined by the following equation (Gaing, 2004):

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}}iter \tag{8}$$

where, w_{max} is the initial weight, w_{min} is the final weight, *iter* is the current iteration number, is the

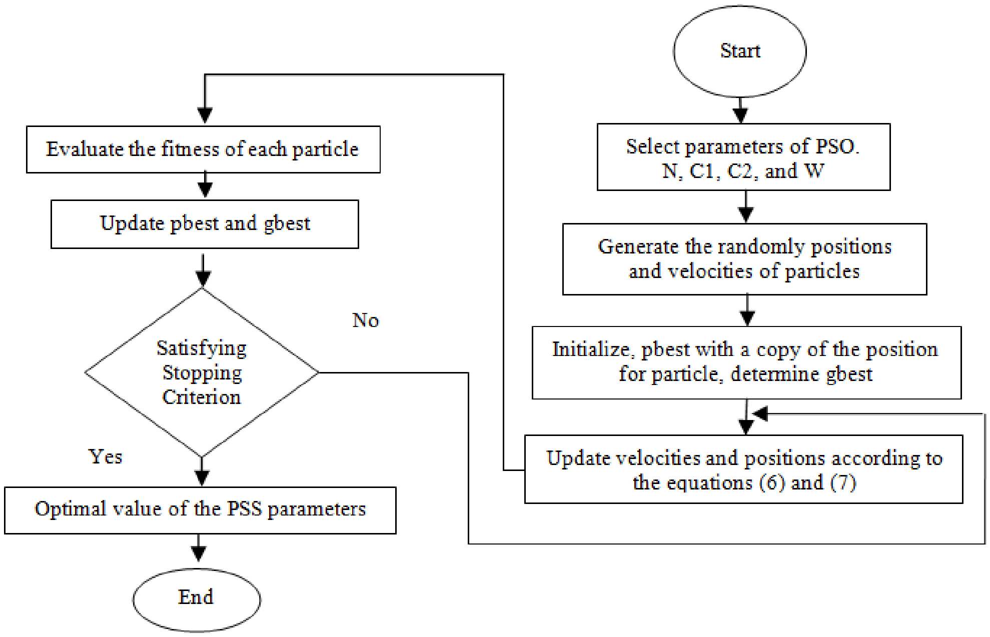

Fig. 1: Particle swarm optimization algorithm

maximum iteration number. The typical range of *w* from 0.9 at the beginning of the search to 0.4 at the end of the search, Fig. 1 shows the flowchart of the PSO algorithm (Rajendraprasad and Panda, 2013). In this study, the PSS design problem is formulated as an optimization problem and solved by PSO method to improve optimization synthesis and find the global optimum value of the fitness function. Selection of a desirable fitness function is very important to optimize PSS parameters. Because, different fitness functions promote different PSO based on PSS behaviors (Manisha *et al.*, 2013).

The PSS controller is optimized by minimizing the objective function (J) in order to improve the system response in terms of oscillation and settling time. Despite there are several methods to come up with the improvement of the performance of the control system (GirirajKumar *et al.*, 2010), such as Integral of Squared Error (ISE), Integral of Time weighted Squared Error (ITSE), Integral of Absolute Error (IAE) and Integral of Time weighted Absolute value of Error (ITAE):

$$J_{ISE} = \int_{0}^{Tsim} \Delta\omega^2(t)dt \tag{9}$$

$$J_{IAE} = \int_{0}^{Tsim} |\Delta\omega(t)|dt \tag{10}$$

$$J_{ITAE} = \int_{0}^{Tsim} t|\Delta\omega(t)|dt \tag{11}$$

$$J_{ITSE} = \int_{0}^{Tsim} t\Delta\omega^2(t)dt \tag{12}$$

In this study, the ITSE of the speed deviation Δω is used as the fitness function (J) which is determined as:

$$J = \int_{t=0}^{Tsim} \Delta\omega^2.t.dt \tag{13}$$

For which $\Delta\omega$ is the speed deviation in radians per seconds and t_{sim} is the range of time for the simulation. The nonlinear model was conducted for the time domain simulation over the simulation period which is aimed at minimizing the fitness function so that the system response such as settling time and overshoots and the constraints are the boundaries of PSS parameters. The transfer function of the i^{th} PSS is given by (Hasan *et al.*, 2012):

$$u_{pssi}(s) = K_i \frac{sT_{Wi}}{1+sT_{Wi}} \left(\frac{(1+sT_{1i})(1+sT_{3i})}{(1+sT_{2i})(1+sT_{1i})} \right) \Delta\omega_i(s) \tag{14}$$

where,

K = PSS gain
T_{wi} = Washout Time constant
T_{1i}, T_{2i}, T_{3i}, T_{4i} = Time constants

Time Constants $T_{1i} = T_{3i}$, $T_{2i} = T_{4i}$ (Identical Phase Compensator Block).

The block diagram of the conventional PSS is shown in Fig. 2, in which case the generator rotor speed

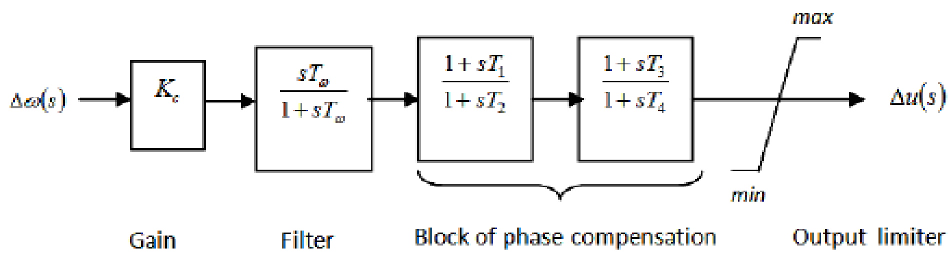

Fig. 2: Block diagram of the conventional power system stabilizer

deviation is used as the only stabilizing signal. The Conventional PSS consists of an amplifier, a washout filter and two lead-lag compensators (Hasan *et al*., 2012).

The PSS parameters to be tuned within their boundaries are formulated as follows (Sanjeev and Chaturvedi, 2013).

Optimize J.

Subject to:

$$K_i^{\min} \le K_i \le K_i^{\max}$$
$$T_{1i}^{\min} \le T_{1i} \le T_{1i}^{\max}$$
$$T_{2i}^{\min} \le T_{2i} \le T_{2i}^{\max}$$

where,

$K^{min}{}_i$ and $K^{max}{}_i$ = The lower and upper bounds of gains PSS

$T^{min}{}_{ji}$ and $T^{max}{}_{ji}$ = The lower and upper bounds of the time constants of all controllers

Fuzzy sliding mode controller: Fuzzy controller design includes the definition the following parameters: Number of partitions of input space and output membership functions, rule base, inference method, fuzzification and defuzzification (Ben-Meziane *et al*., 2013).

In this section, the fuzzy sliding mode controller with varying control gain α_f is presented. More specifically, a fuzzy inference system is used to adjusting the control gain α_f in order to improve the performance of the controller. The rules in the rule base are in the following form (Amer *et al*., 2011):

$$If \;\; e \;\; is \;\; A_i^m \;\; and \;\; \dot{e} \;\; is \;\; B_i^m, \; Then \;\; \alpha_i \;\; is \;\; C_i^m$$

where, $A^m{}_i$, $B^m{}_i$ and $C^m{}_i$ are fuzzy sets. The fuzzy variables input are defined for the rule base as, (e, $\dot{e}$) = {*NB*, *NM*, *NS*, *Z*, *PS*, *PN*, *PB*} and the fuzzy output is (α_f) = {*VVS*, *VS*, *S*, *M*, *B*, *VB*, *VVB*}.

The membership functions for input and output variable are triangular given in Fig. 3 to 5. The 49 rules described presented in a matrix called matrix inference given in the following Table 1 (Amer *et al*., 2011).

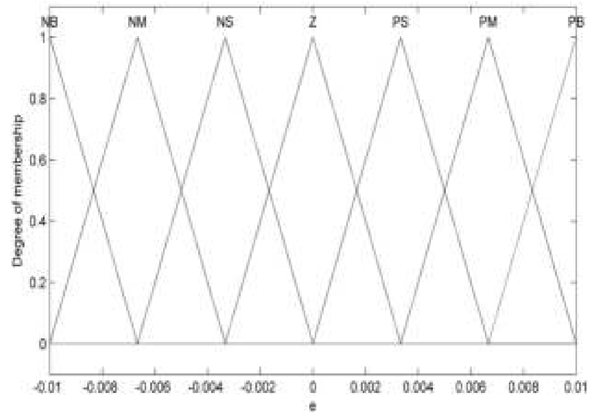

Fig. 3: Membership functions of error

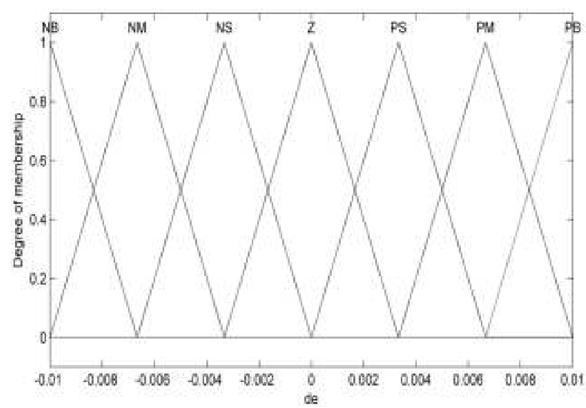

Fig. 4: Membership functions of change of error

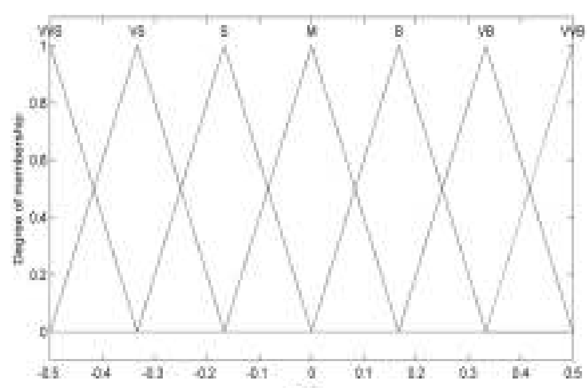

Fig. 5: Membership functions of α_f

Table 1: Rule matrix of the fuzzy inference system

	e (t)						
α_f ė (t)	NB	NM	NS	Z	PS	PM	PB
NB	M	S	VS	VVS	VS	S	M
NM	B	M	S	VS	S	M	B
NS	VB	B	M	S	M	B	VB
Z	VVB	VB	B	M	B	VB	VVB
PS	VB	B	M	S	M	B	VB
PM	B	M	S	VS	S	M	B
PB	M	S	VS	VVS	VS	S	M

THE PROPOSED CONTROL DESIGN

Sliding mode control: Sliding mode control is a nonlinear control solution and a Variable Structure Control (VSC) derived from the variable structure system theory (Ouassaid *et al*., 2011). SMC is known to be robust against fluctuations. It was successfully applied to electric motors, robot manipulators, power systems and power converters. In this section, we will present the general principle of the SMC and the controller design principle. Let us consider the nonlinear system represented by the following state equation (Abera and Bandyopadhyay, 2008):

$$\dot{x} = f(x,t) + g(x,t)u(t) \tag{15}$$

The continuous component insures the motion of the system on the sliding surface whenever the system is on the surface. The equivalent control that maintains the sliding mode satisfies the condition:

$$\dot{S} = 0 \tag{16}$$

$$\begin{aligned} e_i &= \delta_i - \delta_{ir} = x_{i1} - x_{i1r} \\ \dot{e}_i &= x_{i2} \\ \ddot{e}_i &= a_i - b_i x_{i2} - c_i x_{i3}^2 - d_i x_{i3} I_{q_i} \end{aligned} \tag{17}$$

For i = 1, 2 … n.
Let the tracking error vector be $e_i = \left[e, \dot{e}, ..., e^{(n-1)}\right]$.

The relative degree is $r = 3$ then, the switching function can be written as (Abera and Bandyopadhyay, 2008):

$$S(e) = k_1 e + k_2 \dot{e} + \ddot{e} \tag{18}$$

where, $k = [k_1, k_2, 1]^T$ are the coefficients of the Hurwitz Polynomial:

$$h(\lambda) = \lambda^2 + k_2\lambda + k_1 \tag{19}$$

$$\dot{S}(e) = k_1\dot{e} + k_2\ddot{e} + \dddot{e} = k_1\dot{e} + k_2\ddot{e} + f(x) + g(x)u \tag{20}$$

If $f(x)$ and $g(x)$ are known, we can easily construct the sliding mode control:

$$u^* = u_{eq} + u_{smc} \tag{21}$$

$$u_{eq} = \frac{-1}{g(x)}\left(f(x) + k_1\dot{e} + k_2\ddot{e}\right) \tag{22}$$

The fuzzy sliding mode control term is:

$$u_{smc} = \frac{-1}{g(x)}\alpha \operatorname{sgn}(S) \tag{23}$$

The control input u_{smc} to get the state δ to track δ_r is then made to satisfy the Lyapunov-like function:

$$V = \frac{1}{2}s^2 \tag{24}$$

By the following sliding condition:

$$\frac{1}{2}\frac{d}{dt}s^2 \le -\eta|s| \tag{25}$$

where,

$$\operatorname{sgn}(s) = \begin{cases} +1, & if\ s > 0 \\ -1, & if\ s < 0 \end{cases} \tag{26}$$

Fuzzy sliding mode control combined with PSS based on PSO: The control law used in this study is composed of three terms, the nominal control u_{eq}, the robust term represented by the fuzzy sliding mode controller u_{fsmc} and the regulator PSS optimized by the PSO algorithm u^*_{pss}:

$$u = u_{eq} + u_{fsmc} + u^*_{pss} \tag{27}$$

$$u_{eq} = \frac{-1}{g(x)}\left(f(x) + k_1\dot{e} + k_2\ddot{e}\right) \tag{28}$$

$$u_{fsmc} = \frac{-1}{g(x)}\alpha_f sgn(s) \tag{29}$$

where, α_f is the gain of sliding mode controller tuned by a fuzzy logic rule base:

$$u = \frac{-1}{g(x)}\left(f(x) + k_1\dot{e} + k_2\ddot{e} + \alpha_f sgn(s)\right) + u^*_{pss} \tag{30}$$

The combination between the two controllers, fuzzy sliding mode controller with Power System Stabilizer based on PSO algorithm, enhances the damping of the oscillations and the stability of the network.

SIMULATION OF MULTIMACHINE POWER SYSTEM

To evaluate the performance of the proposed control, we performed simulation for the three-machine nine-bus power system as in Fig. 6, with the aim to compare the performance of the proposed controller with SMC controller and the conventional PSS. Detail of the system data are given in Table 2 (Colbia-Vegaa *et al*., 2008).

The following equilibrium point:

$X_{ir} = (x_{i1r}, x_{i2r}, x_{i3r}) = [\delta_i\ \Delta\omega_i\ E'_{qi}]$ for i = 1, 2, 3 of the three-machine system is considered:

$$x_{11r} = 0.0396,\ x_{12r} = 0,\ x_{13r} = 1.0566$$
$$x_{21r} = 0.3444,\ x_{22r} = 0,\ x_{23r} = 1.0502$$
$$x_{31r} = 0.2300,\ x_{32r} = 0,\ x_{33r} = 1.017$$

Furthermore, the topology of the network has been represented by the conductance nodal matrix G and by the susceptance nodal matrix B:

$$G = \left[G_{ij}\right] = \begin{bmatrix} 0.8453 & 0.2870 & 0.2095 \\ 0.2870 & 0.4199 & 0.2132 \\ 0.2095 & 0.2132 & 0.2770 \end{bmatrix}$$

$$B = \left[B_{ij}\right] = \begin{bmatrix} -2.9882 & 1.5130 & 1.2256 \\ 1.5130 & -2.7238 & 1.0879 \\ 1.2256 & 1.0879 & -2.3681 \end{bmatrix}$$

In this case, the control law used constituted by the nominal control, sliding mode control and power system stabilizer. The control parameters of sliding mode control used are $\alpha_i = 0.03$ for i = 1, 2, 3. The specified parameters of the PSS that are used in this study given

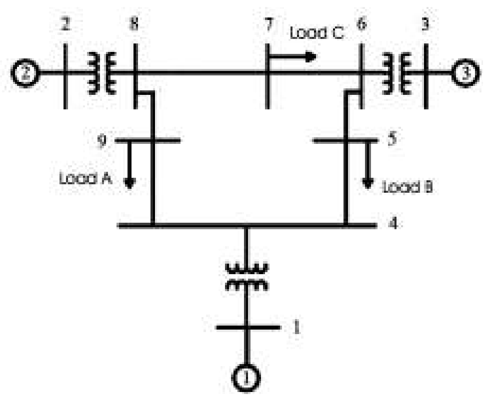

Fig. 6: Three-machine nine-bus power system

Table 2: Nominal parameters values

Parameters	Gen 1	Gen 2	Gen 3
H	23.6400	6.4000	3.0100
X_d	0.1460	0.8958	1.3125
X'_d	0.0608	0.7798	0.1813
D	0.3100	0.5350	0.6000
P_m	0.7157	1.6295	0.8502
T'_{do}	8.9600	6.0000	5.8900

Table 3: Conventional PSS parameters

Parameters	Kp	T1	T2	Tw
PSS-1	7.39	0.17	0.29	10
PSS-2	5.46	0.11	0.26	10
PSS-3	5.33	0.10	0.27	10

Table 4: Performance indices of the controllers

	The proposed control	H infinity control	PSS control
ITAE	0.7678	2.4944	13.2693
ITSE	3.850e-005	4.7880e-004	9.9515e-004

Table 5: Parameters used PSO algorithm

PSO parameters	Value
Swarm size	50
Iteration-max	100
c_1, c_2	2.0, 2.0
w_{max}, w_{min}	0.9, 0.4

in Table 3. The coefficients of the Hurwitz Polynomial used in this study for the multimachine power system are: $k_{1i} = 6$; $k_{2i} = 9$; $k_{3i} = 1$.

The simulation results presented in Fig. 7 to 9 shows the occurrence of chattering caused by a poor choice of controller gain.

To demonstrate performance robustness of the proposed method, two performance indices: the Integral of the Time multiplied Absolute value of the Error (ITAE) and the Integral of Time weighted Squared Error (ISTE) based on the system performance characteristics are being used as:

$$ITAE = \int_0^T t(|\Delta\omega_1| + |\Delta\omega_2| + |\Delta\omega_3|)dt \qquad (31)$$

$$ITSE = \int_0^T \left(\Delta\omega_1^2(t) + \Delta\omega_2^2(t) + \Delta\omega_3^2(t)\right).t.dt \qquad (32)$$

More than the values of the performance indices ITAE and ISTE are lower, the response of the system in time domain is better. Numerical results of these indices for all cases are presented in Table 4.

The parameters used in PSO algorithm are given in Table 5. Control parameters and their boundaries are given below:

$$0 < K_i < 70$$
$$0.01 < T_{1i} < 1$$
$$0.01 < T_{2i} < 1$$

The aim is to compare the performance of the conventional PSS, the sliding mode control and the

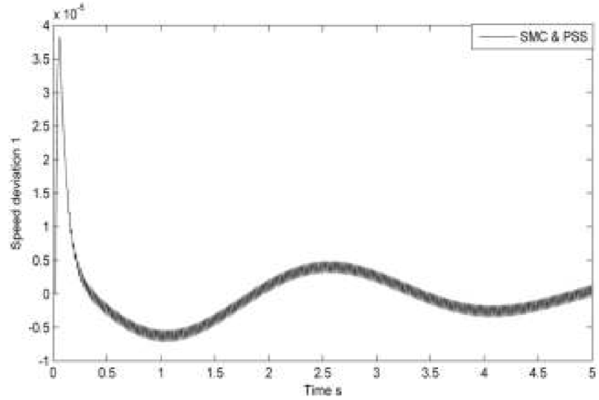

Fig. 7: Deviation speed Δw1

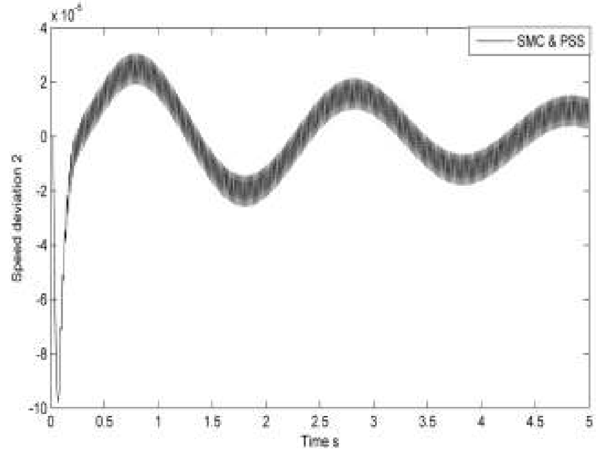

Fig. 8: Deviation speed Δw2

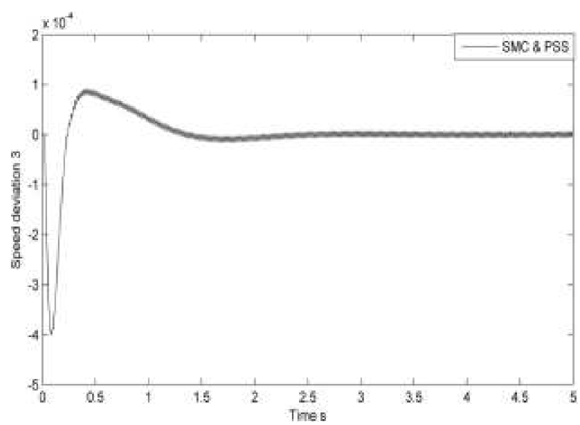

Fig. 9: Deviation speed Δw3

Table 6: Optimized PSS parameters by PSO algorithm

Parameters	Kp	T1	T2
PSS-PSO-1	7.6881	0.2395	0.4550
PSS-PSO-2	3.4404	0.3615	0.2119
PSS-PSO-3	0.8489	0.4417	0.1612

control law proposed in this study composed by the three terms: the nominal control, the robust term FSMC and the PSS optimized by PSO algorithm. The nonlinear

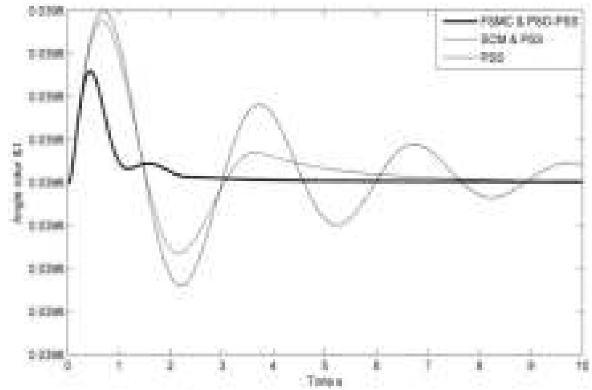

Fig. 10: Rotor angle δ1

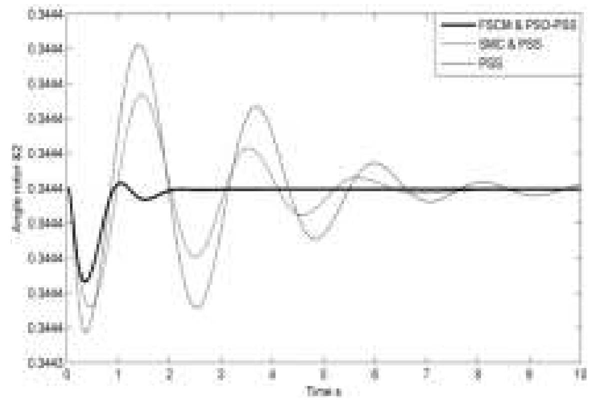

Fig. 11: Rotor angle δ2

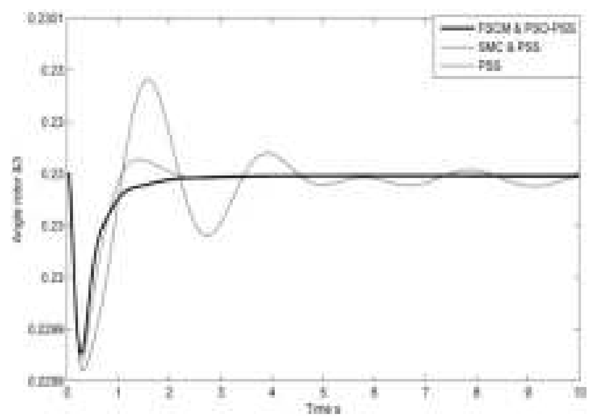

Fig. 12: Rotor angle δ3

simulation results demonstrated that the proposed control is capable of guaranteeing the robust performance of the multimachine power system for a wide range of operating conditions (Table 6).

In this case, the washout time of the PSS T_{wi} = 10 and the control parameters of sliding mode control used are $\alpha_i = 0.0001$ for i = 1, 2, 3.

With the proposed control, the mechanical variables such as the angles rotor (δ_1, δ_2) and the deviation speed ($\Delta\omega_1$, $\Delta\omega_2$) in the generators (G1 and

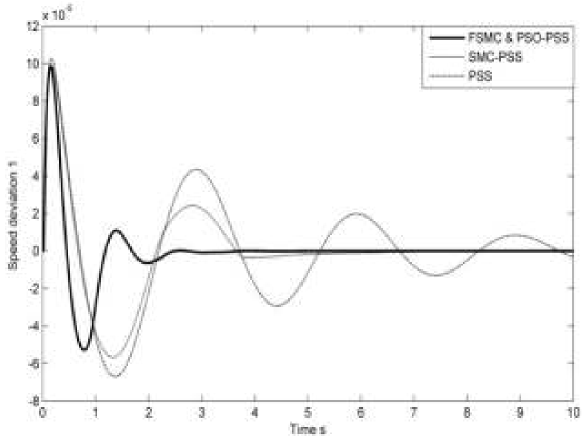

Fig.13: Deviation speed Δw1

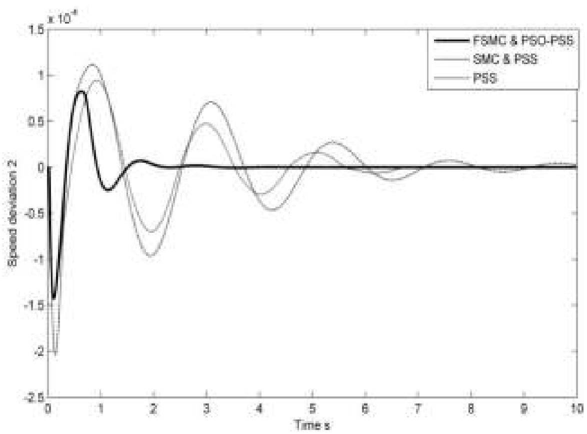

Fig. 14: Deviation speed Δw2

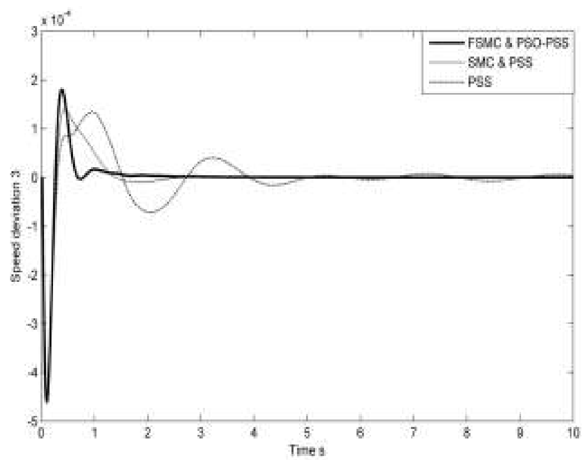

Fig. 15: Deviation speed Δw3

G2) are stabilized in 2.5 sec; see Fig. 10 to 14. For the third generator (G3), the angle rotor δ_3 and the deviation speed $\Delta\omega_3$ are stabilized in 2 and 1.5 sec, respectively; see Figure 12 and 15. The conventional PSS controller requires more time and more oscillations before the same variables are stabilized. Implemented results in this section have demonstrated a superior performance of FSMC in terms of chattering or smoother control action as compared with the normal SMC design.

CONCLUSION

In this study, the proposed control provides an efficient solution to damp the Low frequency oscillations in the multimachine power system and eliminates the chattering in sliding mode control. The design problem of the robustly PSS parameters selection is solved by a PSO algorithm, which enhances the stability of the power system. Also, the robustness and the performance of the fuzzy sliding mode controller design has been proved and evaluated by the dynamic simulation responses of the multimachine power system.

NOMENCLATURE

δ	:	Rotor angle
ω	:	Rotor speed (pu)
$\Delta\omega$	:	The speed deviation
Pm	:	Mechanical input power
Pe	:	Electrical output power (pu)
M	:	System inertia (Mj/MVA)
E'q	:	Internal voltage behind x'd (pu)
Efd	:	Equivalent excitation voltage (pu)
X'd	:	Transient reactance of d axis (pu)
Xq	:	Steady state reactance of q axis (pu)
Xd	:	Steady state reactance of d axis (pu)
T'do	:	Time constant of excitation circuit (s)
T_{sim}	:	Simulation time (s)
Tw	:	Washout filter (s)
T1-T4	:	Time constants of lead-lag dynamic compensator (s)
K	:	Gain of the Stabilizer
PSS	:	Power System Stabilizer
PSO	:	Particle Swarm Optimization
SMC	:	Sliding Mode Controller
FSMC	:	Fuzzy Sliding Mode Controller

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