Particle Swarm Optimization Based Power System Stabilizer to Reduce Generator Rotor Oscillations

A. Jeevanandham[1] K. Thanushkodi[2]

Abstract –A classical lead-lag power system stabilizer is used for demonstration in this paper. Initially single first-order phase compensation block is considered. The stabilizer parameters are selected in such a manner to damp the rotor oscillations. The problem of selecting the stabilizer parameters is converted to a simple optimization problem with an eigen value based objective function and it is proposed to employ particle swarm optimization for solving optimization problem. The objective function allows the selection of the stabilizer parameters to optimally place the closed-loop eigen values in the left hand side of the complex s-plane. The effectiveness of the stabilizer tuned using the above technique, in enhancing the stability of power system. Stability is confirmed through eigen value analysis and simulation of results for the best performance of the system.

Keywords – Power system stability, rotor oscillations, robust control, particle swarm optimization

I. INTRODUCTION

During changes in operating conditions, oscillations of small magnitude and low frequency often persist for long period of time and in some cases even present limitations on power transfer capability. Power system stabilizer (PSS) is designed to damp the low frequency oscillations of power system [1].

PSS is used to add damping to the generator rotor oscillations by controlling its excitation using auxiliary stabilizing signals. The widely used conventional power system stabilizer (CPSS) is designed using the theory of phase compensation and introduced as a lead-lag compensator [7].

An inter connected power system, depending on its size, has hundreds to thousands of modes of oscillation. In the analysis and control of system stability, two distinct types of system oscillations are usually recognized. One type is associated with units at a generating station swinging with respect to the rest of the power system. Such oscillations are referred to as local plant mode oscillations. The frequencies of these oscillations are typically in the range of 0.8 to 2.0 Hz. The second type of oscillations is associated with the swinging of many machines in one part of the system against machines in the other parts. These are referred to as inter area mode oscillations, and have frequencies in the range of 0.1 to 0.7 Hz.

The basic function of PSS is to add damping to both types of system oscillations.
Other modes which may be influenced by PSS include torsional modes and control modes such as the exciter mode associated with the excitation system and the field circuit [5]. The over all excitation control system is designed so as to maximize the damping of the local plant mode as well as inter-area mode oscillations with out compromising the stability of other modes and to enhance system transient stability. Input to PSS is rotor speed deviation which results damping torque.

II. CONTROLLER DESIGN

Damping torque is produced to overcome rotor oscillation. The action of a PSS is to extend the angular stability limits of a power system by providing supplemental damping to the oscillation of synchronous machine rotors through the generator excitation [3].

Controller is designed to compensate lag between exciter input (ΔV_s) and electrical torque (ΔT_{pss}).

$$\frac{\Delta T_{PSS}}{\Delta V_S} = K\angle -\theta \qquad (1)$$

The amount of damping introduced depends on the gain of $\Delta\omega_r$ ransfer function at that particular fı ΔV_S y of oscillation.

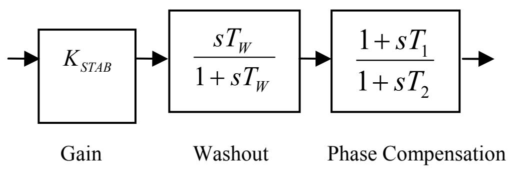

Fig. 1: Lead – lag power system stabilizer

A. Phase Lead Compensation

To provide damping, the stabilizer must produce a component of electrical torque which is in phase with speed variations. Therefore, the PSS transfer function should have an appropriate phase-lead characteristics to compensate for the phase lag between the exciter input and the electrical torque.

The phase characteristic has to be compensated changes with system conditions. Therefore, a compromise must be made and a characteristic acceptable for a desired range of frequencies (normally 0.1 to 2.0 Hz) and for different system conditions is selected. This may result in less than optimum damping at any one frequency. Generally, slight under compensation is preferable to overcompensation so that both damping and synchronizing torque components are increased.

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B. Stabilizing Signal Washout

The signal washout function is a high pass filter which removes dc signals, and without it steady changes in speed would modify the terminal voltage. The washout time constant is in the range of 1 to 20 seconds. For local mode oscillation, a wash out of 1 to 2 sec is satisfactory. From the view point of low frequency inter area oscillations a washout time constant of 10 sec or higher may be required in order to reduce phase lead at low frequencies.

C. Stabilizer Gain

The stabilizer gain (K_{STAB}) is chosen by examining the effect for a wide range of values. Ideally, the stabilizer gain should be set at a value corresponding to maximum damping. Gain is set to a value which results in satisfactory damping of the critical system mode(s) without compromising the stability of other modes, or transient stability, and which does not cause excessive amplification of stabilizer input signal noise.

D. Stabilizer Output Limits

In order to restrict the level of generator terminal voltage fluctuation during transient conditions, limits are imposed on the PSS output. The effect of the two limits is to allow maximum forcing capability while maintaining the terminal voltage within the desired limits [3].

III. Problem Formulation

In this section, the eigen value-based objective function used to robustly select the PSS parameters [2], and the optimization problem solved with particle swarm optimization.

Consider the problem of determining the parameters of a stabilizer that relatively stabilizes a family of *N* plants,

$$\dot{X}(t) = A_k X(t) + B_k U(t);\quad k = 1,2,3,...N \qquad (2)$$

where $\dot{X}(t) \in R^n$ is the state vector and $X(t) \in R^m$ is the control vector.

Very often, the closed-loop modes are specified to have some degree of relative stability. In this case closed-loop eigen values are constrained to lie to the left of a vertical line corresponding to a specified damping factor.

A necessary and sufficient condition for the set of plants in equation (2) to be simultaneously relatively stabilizable with a single control law is that the eigen values of the closed-loop system lie in the left-hand side of a vertical line in the complex s-plane. This condition motivates the following approach for determining the parameters of the PSS.

Select the parameters of the PSS to minimize the following objective function:

$$J = \max\{\mathrm{Re}(\lambda_{k,i}) + \beta\};\ k = 1,2,3,...N;\ i = 1,2,...n \qquad (3)$$

where $\lambda_{k,i}$ is i^{th} closed loop eigen value of the k^{th} plant and β is relative stability factor. Subject to the constraints that finite bounds are placed on the stabilizer parameters.

In this paper instead of N number of plants, single-machine-infinite-bus system is considered. The objective function can be modified as,

$$J = \max\{\mathrm{Re}(\lambda_k) + \beta\} \qquad (4)$$

The relative stability is determined by the value of β as shown in Fig. 2

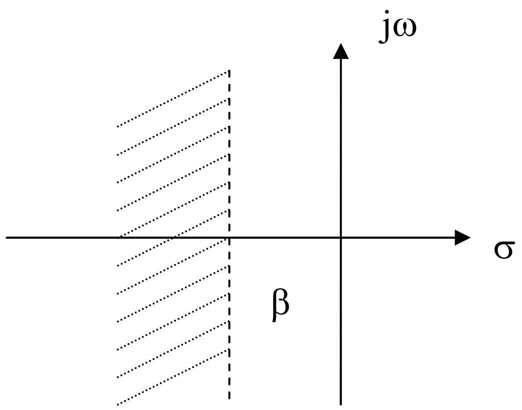


Fig. 2: Region in the left-hand side of a vertical

Plainly, if a solution is found such that $J < 0$, then the resulting parameters simultaneously relatively-stabilize the collection of plants. The existence of a solution is verified numerically [2] by minimizing *J*.

IV. System Model

In this steady single-machine-infinite-bus power system is considered [9]. The supplementary stabilizing signal considered is one proportional to speed [6]. A widely used conventional PSS is considered throughout the study.

The transfer function of PSS with single phase compensation block is

$$\frac{\Delta V_S}{\Delta \omega_r} = K_{STAB} \frac{sT_W}{1 + sT_W} \frac{1 + sT_1}{1 + sT_2} \qquad (5)$$

The first term is stabilizer gain. The second term is washout term with a time lag T_w. The third term is a lead compensation [3] to improve the phase lag through the system. The numerical values of T_w, T_2 and system data are given in Appendix I. The remaining parameters namely K_{STAB} and T_1 are assumed to be adjustable parameters. The optimization problem is selection of these PSS parameters easily and accurately. The optimization problem can be solved using the particle swarm optimization. The PSO algorithm in explained in Appendix II.

For a given operating point, the power system is linearized around the operating point, the eigen values of the closed-loop system are computed, and the objective function is evaluated. It is worth mentioning that only the system electromechanical modes are incorporated in the objective function. The bounds on the parameters used in the PSO are given in Appendix I.

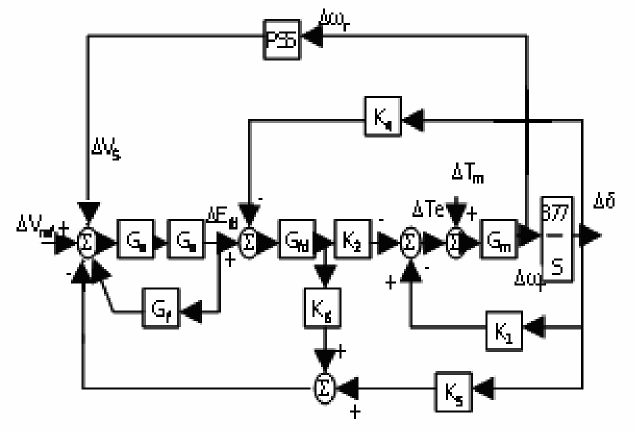


Fig. 3: Block diagram of AVR with PSS

The system with multivariable state space model [11] for individual generator may be considered in a multimachine system and the PSS parameters can be tuned by using the PSO. In our case the state space model for SMIB system [9] is considered.

V. Particle Swarm Optimization

Similar to evolutionary algorithms, the PSO technique conducts searches using a population of particles, corresponding to individuals. In a PSO system [10], particles change their positions by flying around in a multidimensional search space until a relatively changed position has been encountered, or until computational limitations are exceeded.

The following are the advantages of PSO [8] over other traditional optimization techniques.

- PSO is a population based search algorithm. This property ensures it to be less susceptible to getting trapped on local minima.
- PSO uses payoff (performance index or objective function) information to guide the search in the problem space.
- PSO uses probabilistic transition rules and not deterministic rules. Hence, PSO is a kind of stochastic optimization algorithm that can search a complicated and uncertain area.

A. Particle X(t):

It is a candidate solution presented by an m-dimensional real-valued vector, where m is the number of optimized parameters.

B. Population pop(t):

It is a set of n particles at time t.
(i.e. pop(t) = $[X_1(t), X_2(t), \ldots, X_n(t)]^T$)

C. Swarm:

It is disorganized population of moving particles that tend to cluster together while each particle seems to be moving in a random direction.

D. Particle velocity V(t):

It is the velocity of the moving particles represented by an m-dimensional real valued vector. At the time t, the jth particle velocity $V_j(t) = [v_{j,1}(t), v_{j,2}(t), \ldots, v_{j,m}(t)]$, where $v_{j,k}(t)$ is the velocity component of jth particle with respect to the kth dimension.

E. Individual best $X^*(t)$:

As the particle moves through the search space, it compares its fitness value at the current position to the best fitness value it has ever attained at any time up to the current time. The best position that is associated with the best fitness encountered so far is called is called individual best $X^*(t)$. For each particle in the swarm, $X^*(t)$ can be determined and updated during the search. In a minimization problem objective function J, the individual best of the jth particle $X_j^*(t)$ is determined so that $J(X_j^*(t)) \le J(X_j^*(\tau), \tau \le t$. For simplicity, assume that $J_j^* = J(X_j^*(t))$. For the jth particle, individual best can be expressed as $X_j(t) = [x^*_{j,1}(t), x^*_{j,2}(t), \ldots, x^*_{j,m}(t)]$.

F. Global best $X^{**}(t)$:

It is the best position among all of the individual best positions achieved so far. Hence, the global best can be determined such that $J(X^{**}(t)) \le J(X_j^*(t)), j = 1,2,\ldots n$. For simplicity, assume that $J^{**} = J(X^{**}(t))$.

G. Stopping criteria:

These are the conditions under which the search process will terminate. In this study, the search will terminate if one of the following criteria is satisfied,

a) The number of iterations since the last change of the best solution is greater than a prespecified number

b) The number of iterations reaches the maximum allowable number.

The particle velocity in the kth dimension is limited by some maximum value, v_k^{max}. This limit enhances the local exploration of the problem space and it realistically simulates the incremental changes in human learning. The maximum velocity in the kth dimension is characterized by the range of the kth optimized parameter and given by

$$v_k^{\max} = \frac{\left(x_k^{\max} - x_k^{\min}\right)}{N}$$

where N is a chosen number of intervals in the kth dimension.

VI. Simulation Results

In this part of the study, a single machine is connected to infinite bus through a transmission line, and operating at different loading conditions [4], is considered. The linearized model of this system, voltage regulator and exciter included [10] is considered.

The constants K_1 to K_6, with the exception of K_3, which is only a function of the ratio of impedance, are dependent on the actual real power (P) and reactive power (Q) loading as well as the excitation levels in the machine.

The operating points are selected based on the different loading conditions. The simultaneous damping enhancement of demonstrated by considering five different loading conditions.

The operating points were selected randomly as follows:
(Po , Qo) = (0.9, 0.3) ; (0.8, -0.1); (0.5,0.5) ; (0.6, -0.2)
(1.0, 0.6)

The eigen values are found by transferring the transfer function of the system data into state space model.

The eigen values of the system at the five operating points considered, with out PSS are,

1. 0.4981 ± 6.6288i, -33.6805, -17.3597
2. 0.7513 ± 7.3702i, -11.5526, -39.9942
3. 0.0283 ± 5.3580i, -25.0504 ± 9.1822i
4. 0.1936 ± 6.9157i, -10.7786, -39.6528
5. 0.5410 ± 6.1171i, -21.6341, -29.4919

From the eigen values it is clear that the system is unstable due to its location in the right half of the *s* – plane.

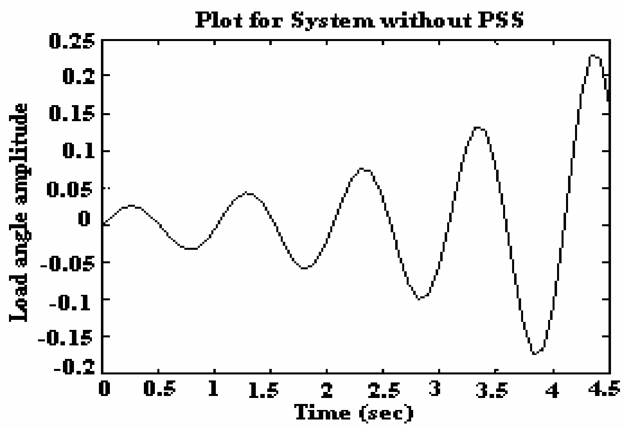


Fig. 4: Response of the system without PSS

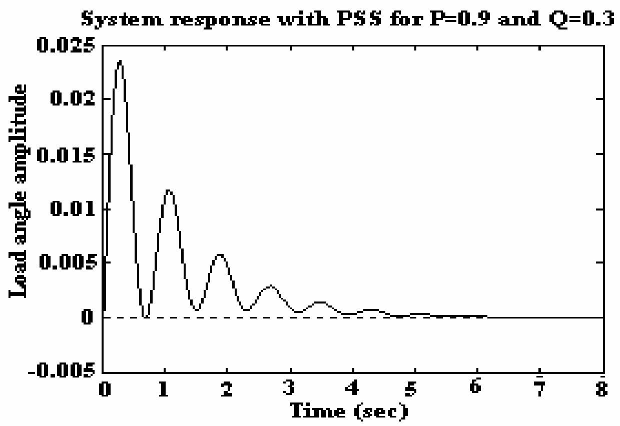
For the system to be stable the real part of eigen value should be located in the in the left hand side of s-plane.

The objective function *J* is optimized with the PSO and *N*=5 to shift the electromechanical mode of each of the five systems to the left of the vertical line defined by β = -2.2.

The eigen values of the five systems, with PSS are

1. -34.1670±5.0796i, -9.9855, -0.9887± 7.7731i,-0.7644
2. -37.4972,-35.6751, -0.5533±9.3491i, -6.0033,-0.7792
3. -29.0306±7.0224i, -20.4992,-0.8755±5.6109i,-0.7500
4. -36.4206±0.9044i, -1.3020±9.2146i, -4.8165, -0.7998
5. -33.0536±5.8900i,-12.5555, -0.8183±6.9006i,-0.7620

All the eigen values of the system were located in the left half of the *s* – plane. So the system will be stable.



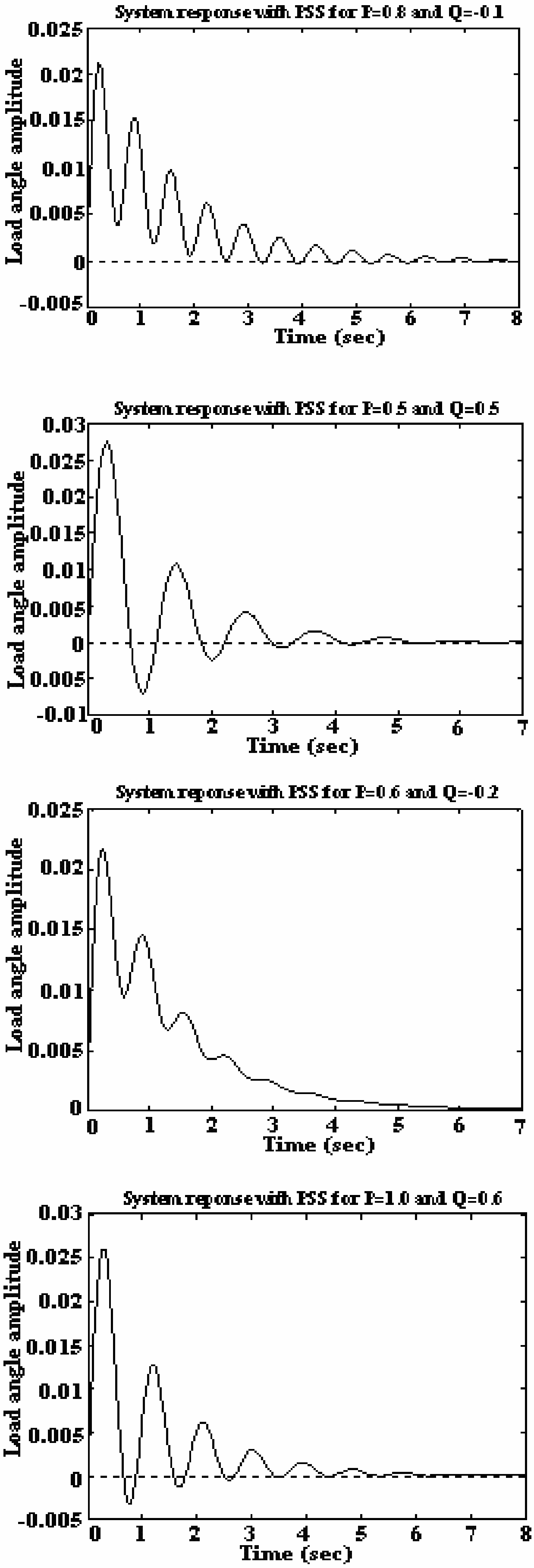


Fig. 5: Response of the system with PSS using particle swarm optimization

Fig. 5 shows response of the system with power system stabilizer for various operating conditions whereas their parameters were tuned by using Particle Swarm Optimization (PSO). It is indicating simultaneous improvement in the response of the five systems.

The above two techniques can be compared as shown in Table 1.

Table 1: Comparison between conventional method and particle swarm optimization

Loading Condition (Po , Qo)	Conventional Method		Particle Swarm Optimization	
	Settling Time in Sec.	Peak Amp.	Settling Time in Sec.	Peak Amp.
0.9, 0.3	20.8	0.0443	4.51	0.0236
0.8, -0.1	7.6	0.0313	6.32	0.0211
0.5, 0.5	5.58	0.0287	4.92	0.0275
0.6, -0.2	6.96	0.0272	5.06	0.0218
1.0, 0.6	5.09	0.0324	4.99	0.026

From the above comparison the Particle swarm optimization technique is having lower settling time, lower peak amplitude and lesser computational time than conventional method. Moreover by using PSO the eigen values are located far away in the left hand side of s-plane to make the system more stable. So tuning of PSS parameters by using PSO is more optimal than conventional technique.

VII. CONCLUSION

The use of PSO to design robust power system stabilizers for power systems working at various operating conditions are investigated in this paper. The problem of selecting the PSS parameters, which simultaneously improve the damping at various operating conditions, is converted to an optimization problem with an eigen value-based objective function which is solved by both conventional and PSO techniques.

The objective function is presented allowing the robust selection of stabilizer parameters that will optimally place the closed-loop eigen values in the left hand side of a vertical line in complex s-plane. By comparing the above two optimization techniques, it is found that Particle Swarm Optimization is better than Conventional method in tuning the parameters of the Power system stabilizer, to reduce intra and inter area rotor oscillations over a wide range of operating conditions.

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APPENDIX I

SYSTEM DATA

A. Single- Machine- Infinite- Bus System:

$$G_m = \frac{1}{2H_S + K_D}; \quad G_A = \frac{K_A}{sT_A + 1}; \quad G_e = \frac{1}{sT_E + 1}$$

$$G_f = \frac{sK_f}{1 + sT_F}; \quad G_{fd} = \frac{K_3}{1 + sT'_{do}K_3}$$

B. Machine (p.u)

$x_d = 1.7$; $x_d' = 0.254$; $x_q = 1.64$; $\omega_0 = 120\,\pi$ rad/s ;
$T_{do}' = 5.9$ sec ; $K_D = 0$; H = 2.37 sec

C. Transmission Line (p.u)

$r_e = 0.02$; $x_e = 0.4$

D. Exciter and Stabilizer

$K_A = 400$; $T_A = 0.05$ sec ; $K_F = 0.025$
$T_F = 1.0$ sec ; $K_E = -0.17$; $T_E = 0.95$ sec
$T_W = 10$ sec ; $T_2 = 0.0227$ sec
Bounds for the stabilizer adjustable gain and time constants are [0.01, 10] and [0.03, 1.0] respectively.

APPENDIX II

PARTICLE SWARM OPTIMIZATION

Step (1): Set the time counter $t = 0$ and generate random n particles, $\{X_j(0),\ j = 1,2,\ldots n\}$, where $X_j(0) = [x_{j,1}(0), x_{j,2}(0), \ldots.\ x_{j,m}(0)]$. $x_{j,k}(0)$ is generated by randomly selecting a value with uniform probability over the kth optimized parameter search space $[x_k^{min},\ x_k^{max}]$.Generate randomly initial velocities of all particles, $\{V_j(0),\ j = 1,2,\ldots n\}$, where $V_j(0) = [v_{j,1}(0),\ v_{j,2}(0), \ldots.\ v_{j,m}(0)]$. $v_{j,k}(0)$ is generated by randomly selecting a value with uniform probability over the kth optimized parameter search space $[-v_k^{max},\ v_k^{max}]$. Each particle in the initial population is evaluated using the objective function, J. For each particle, set $X^*_j(0)=X_j(0)$ and $J^*_j=J_j$, $j=1,2,\ldots,n$. Search for the best value of objective function J_{best}. Set the particle associated with J_{best} as the global beat, $X^{**}(0)$, with an objective function of J^{**}. Set the initial value of the inertia weight $w(0)$.

Step (2): Update the time counter $t = t+1$.

Step (3): Update the inertia weight $w(t) = \alpha\ w(t-1)$.

Step (4): Using the global best and individual best, the jth particle velocity in the kth dimension is updated according to the following equation:

$$v_{j,k}(t) = w(t)v_{j,k}(t-1) + c_1 r_1 (x^*_{j,k}(t-1) - x_{j,k}(t-1) + c_2 r_2 (x^{**}_{j,k}(t-1) - x_{j,k}(t-1))$$

where c_1 and c_2 are positive constants and r_1 and r_2 are uniformly distributed random numbers in [0,1].

Step (5): Based on the updated velocities, each particle changes its position according to the following equation:

$$x_{j,k}(t) = v_{j,k}(t) + x_{j,k}(t-1)$$

Step (6): Each particle is evaluated according to the updated position. $J_j < J^*_j$, $j=1,2,\ldots,n$, then update individual best as $X^*_j(t) = X_j(t)$ and $J^*_j = J_j$, and go to step 7; else go to step 7.

Step (7): Search for the minimum value J_{min} among J^*_j, where min is the index of the particle with minimum objective function value, i.e., min ϵ {j; $j=1,2,\ldots,n$}. If $J_{min} < J^{**}$ then update global best as $X^{**} = X_{min}(t)$, and $J^{**}=J_{min}$ and go to step 8; else go to step 8.

Step (8): If one of the stopping criteria is satisfied, then stop, or else go to step 2.

REFERENCES

[1] M.A. Abido, "Robust design of multi machine power system stabilizers using simulated annealing", IEEE Transactions on Energy Conversion, Vol. 15, No. 3, Sep 2000, pp. 294-304.

[2] M.A. Abido, Y.L. Abdel-Magid and A.H. Mantawy, "Robust tuning of power system stabilizers in multimachine power systems", IEEE Transaction on Power systems, Vol. 15, No. 2, May 2000, pp. 735-740.

[3] P. Kundur, M. Klein, G.J. Rogers and M.S. Zywno, "Application of power system stabilizer for enhancement of over all system stability", IEEE Transaction on Power system, Vol. 4, No. 2, May 1989, pp.614-626.

[4] Michhel J. Gibbard, "Robust design of fixed-parameter power system stabilizers over a wide range of operating conditions", IEEE Transactions on Power system, Vol. 6, No. 2, May 1991, pp.794-800.

[5] Ali Feliachi, Xiaofan Zhang, Craig S.Sims, "Power System stabilizers design using optimal reduced order models part I and part II", IEEE Transactions on Power system, Vol. 3, No. 4, Nov 1988, pp.1670-1684.

[6] F.P. De Mello and C.Concordia, "Concepts of synchronous machine stability as affected by excitation control", IEEE Transactions on Power Apparatus and Systems, Vol. PAS-92, 1968, pp. 1426-4134.

[7] E.V. Larsen and D.A. Swann, "Applying Power System Stabilizers: Parts I, II, and III", IEEE Transactions on Power Apparatus and Systems, Vol. PAS-100, 1981, No 6, pp. 3017-3046.

[8] M. A. Abido, "Optimal design of power system stabilizers using particle swarm optimization", IEEE Transactions on Energy Conversion, Vol. 17, No. 3, Sep 2002, pp. 406-413.

[9] P. Kundur, Power system stability and control, (McGraw Hill, 1994).

[10] J. Kennedy, R. C.Eberhart and Y. Shi, Swarm Intelligence, Morgan Kaufmann, San Francisco, Calif, USA, 2001.

[11] Bin Wu and O. P. Malik, "Multivariable adaptive control of synchronous machines in a multimachine power system", IEEE Transactions on Power Systems, Vol. 21, No. 4, Nov 2006. pp. 1772-1781.

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