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Full Length Research Paper

Multi-machine power system stabilizer design using improved particle swarm optimization (PSO) with time-varying acceleration coefficients

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An efficient and most famous tool to enhance damping of the power system low frequency oscillations is the conventional widely used lead-lag Power System Stabilizer (PSS). To achieve the desired level of robust performance under transient situation, selecting a suitable design method for optimal tuning of PSS parameters is very important in multi-machine power system. Because, it is a multimodal and difficult combinatorial optimization problem, this paper presents a novel parameter automation strategy for Particle Swarm Optimization (PSO) called PSO with Time-Varying Acceleration Coefficients (PSO-TVAC). This optimization method has a strong ability to successfully control both global and local search in each iteration process for considerably increasing the probability of finding the global optimum solution. The PSO-TVAC algorithm is applied to optimal tuning PSS parameters problem in order to reduce the PSS design effort and find the best possible solution within a reasonable computation time. For this reason, the robustly selection of PSSs parameters is converted as an optimization problem based on the time domain-based objective function under different operating conditions. The robustness of the proposed method is demonstrated on a multi-machine power system in comparison with the classical PSO and conventional method based designed PSSs. It is shown through the nonlinear time domain simulation and some performance indices for a wide range of loading condition. The analysis of the results shows that the improved PSO-TVAC is not only very effective but also provides an excellent ability for damping low frequency oscillations and greatly enhance the dynamic stability of the power system. Moreover, the proposed PSO-TVAC algorithm is superior than that of the classical PSO one in terms of accuracy, convergence and computational effort.

Key words: Power system stabilizer (PSS) design, particle swarm optimization, power system dynamics, time-varying acceleration coefficients.

INTRODUCTION

Transient and dynamic stability considerations are the most important aspects in the reliable and secure efficient operation of power systems. This arises from the fact that the power system must maintain frequency and voltage switching out of a transmission line during a fault (Chompoobutrgool et al., 2011). By the development of levels at the nominal values, under any disturbance, like a sudden increase in the load, loss of one generator or interconnection of large electric power systems, there have been spontaneous system oscillations at very low frequencies in order of 0.2 to 3.0 Hz. Once started, they would continue for a long period of time. In some cases, they continue to grow, causing system separation if no adequate damping is available. Moreover, low frequency oscillations present limitations on the power-transfer capability. To enhance system damping, the generators are equipped with Power System Stabilizer (PSS) that

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provides supplementary feedback stabilizing signals in the excitation system. PSS augments the power system stability limit and extends the power-transfer capability by enhancing the system damping of low frequency oscillations associated with the electromechanical modes (Kundur, 1994).

Valuable research contributions from time to time for the PSS design in the power systems like the adaptive control techniques (Chaturvedi and Malik, 2007; Fraile-Ardanuy and Zufiria, 2007), robust control methodology (Hardiansyah et al., 2006; Segal et al., 2000; Segal et al, 2004), neural networks (Rigatos and Siano, 2011; Werner et al., 2003) and fuzzy logic theory (El-Zonkoly et al., 2009; Hwang et al., 2008; Kvasov et al., 2008) have been represented in the literature. Regardless of the adequate results provided by adaptive controllers, the control strategies are needed on line system model identification and then they are complex for practical application. The gains of robust control techniques are considering physical understudying and uncertainties of the system in the synthesis procedure (Hardiansyah et al., 2006; Segal et al., 2000). However, the importance and difficulties in the choice of weighting functions have been reported. On the other hand, the order of the robust control based stabilizer is high which gives rise to complex structure of such stabilizers and reduces their applicability. It should be noted that, although the transient response of the power system is encouraged by the ANN based controller (Rigatos and Siano, 2011; Werner et al., 2003), but these controllers have the long training time and choosing the number of layers and number of neurons in each layers problem. Fuzzy logic based PSSs are model-free stabilizers; that is, they do not require an exact mathematical model of the controlled system (Hwang et al., 2008; Kvasov et al., 2008). Furthermore, effectiveness and speed are the most important properties than the other classical methods. However, it should be pointed out that the fuzzy controllers require two or three dimensional rule base. This problem makes the design synthesis is more difficult.

Despite the potential of the modern control strategies, the Conventional lead-lag Power System Stabilizer (CPSS) structure has been widely used by power system utilities (Gibbard, 1991; Abdel-Magid et al., 2000). The reasons behind that might be the ease of online tuning and the lack of assurance of the stability related to some adaptive or variable structure techniques. On the other hand, Shayeghi et al. (2010) have revealed that the suitable choice of the CPSS parameters provided satisfactory damping performance over a wide range of system loading conditions during the system upsets. It should be noted that the problem of the PSS parameters tuning is a multimodal optimization problem (that is, there exists more than one local optimum). Hence, the conventional optimization methods and local optimization techniques, which are well elaborated upon, are not suitable for this kind of problem. Thus, it is desirable that a novel optimization strategy for optimal tuning of the PSS parameters be developed.

In the recent years, global optimization techniques like Genetic Algorithms (GA) (Sundareswaran and Begum, 2004; Wang et al., 2011), simulated annealing (Abido, 2003), rule based bacteria foraging (Mishra et al., 2007) and strength pareto evolutionary algorithm (Yassami et al., 2010) have been reported for the PSS parameter optimization. These evolutionary based methods are heuristic population-based search procedures that incorporate random variation and selection operators. Although, these methods seem to be good quality solution for the PSS design problem, however, when the system has a extremely epistatic objective function (that is, where optimized parameters are very correlated), and number of parameters to be optimized is more, then they have degraded efficiency to find the global optimum solution and also simulation process takes a lot of computing time. Recently, the classical Particle Swarm Optimization (PSO) based method has been represented for the design of PSS parameters by Shayeghi et al. (2010) and Eslami et al. (2010a). The capability of this method was shown for PSS designing to improve low frequency oscillations damping at different operating conditions than the GA approach on a multi-machine power system. However, it should be noted that the performance of the classical PSO greatly depends on its parameters adjustments, and it often suffers the problem of being trapped in the local optima so as to be premature convergence. Thus, some modification has been proposed for the classical PSO algorithm to improve its performance. An Improved PSO with passive congregation (PSOPC) has been undertaken to solve the PSS design problem by Eslami et al. (2010b) to enrich the information sharing mechanism for effectively enhancement the convergence rate and the accuracy of the classical PSO. Using the numerical results it was shown that PSOPC method has better convergence property and can get better low frequency oscillations than the classical one.

The PSO with time-varying acceleration coefficients (PSO-TVAC) represented by Ratnaweera et al. (2004) is one the best technique for effectively improvements of the classical PSO performance in terms of robustness to control parameters and computational effort. All algorithm parameters including inertia weight and acceleration coefficients are varied with time (iterations) to efficiently control the local search and convergence to the global optimum solution. This strategy is caused to improve the global search in the early stage of the optimization process and cheering the particles to converge toward the global optima at the end of it. Moreover, it was shown that the PSO-TVAC has very few parameters to adjust than other heuristic optimization methods and a higher success convergence rate since it does exploration and exploitation processes together efficiently. Thus, in this paper, the PSO-TVAC optimizer is proposed to optimal tune of the PSSs gain and time constants. It is used to achieve desired level of low frequency oscillations damping and enhance dynamic stability of the multi machine power system. The PSSs parameters are automatically tuned with optimizing a time domain based objective function for a wide range of operation conditions by PSO-TVAC algorithm.

The effectiveness of the proposed method is tested on a multi-machine power system under different operating conditions in comparison with the classical based PSSs (CPSS) and PSO based one through nonlinear time domain simulation and some performance indices. The simulation results demonstrate the robust performance of the proposed method for damping low frequency oscillations than the CPSO and classical method one. Using the proposed algorithm the relative stability is guaranteed and the time domain specifications concurrently secured. This provides a useful promising scheme to choose desirable PSS from a set of optimally tuned PSSs for the system operator, PSS manufacturer and customers.

MATERIALS AND METHODS

PSO review

Kennedy et al. (2001) developed a PSO algorithm based on the behavior of particles or agents of a swarm. Its roots are in zoologist's modeling of the movement of individuals (for example, fishes, birds, or insects) within a group. The PSO algorithm searches in parallel using a group of individuals similar to other AI-based heuristic optimization techniques. A particle in a swarm approaches to the optimum or a quasi optimum through its present velocity, previous experience and the experience of its neighbors (Lin et al., 2010).

In a physical-dimensional search space, the position and velocity of individual i are represented as the vectors $\mathbf{X_i}=(\mathbf{x_{i1}},\ldots,\mathbf{x_{in}})$ and $\mathbf{V_i}=(\mathbf{v_{i1}},\ldots,\mathbf{v_{in}})$ in the PSO algorithm, respectively. Let $\mathrm{Pbest}_\mathbf{i}=(\mathbf{x}_{\mathbf{i1}}^{\mathrm{Pbest}},\ldots,\mathbf{x}_{\mathbf{in}}^{\mathrm{Pbest}})$ and $\mathrm{Gbest}_\mathbf{i}=(\mathbf{x}_{\mathbf{i1}}^{\mathrm{Gbest}},\ldots,\mathbf{x}_{\mathbf{in}}^{\mathrm{Gbest}})$ be the best position of particle i and its neighbors' best position so far. Using this information, the updated velocity of particle is given by:

$$\mathrm{V}_\mathrm{i}^{\mathrm{k+1}}=\omega\mathrm{V}_\mathrm{i}^\mathrm{k}+c_1\mathrm{rand}_1\times\left(\mathrm{Pbest}_\mathrm{i}^\mathrm{k}-\mathrm{X}_\mathrm{i}^\mathrm{k}\right)+c_2\mathrm{rand}_2\times\left(\mathrm{Gbest}^\mathrm{k}-\mathrm{X}_\mathrm{i}^\mathrm{k}\right) \quad (1)$$

Where, $\mathrm{V}_\mathrm{i}^\mathrm{k}$ is velocity of particle at iteration k; ω is inertia weight parameter; c_1 and c_2 are acceleration coefficients factors; X_i^k is position of particle at iteration k; $Pbest_i^k$ is the best position of particle until iteration k and $Gbest_i^k$ is the best position of the group until iteration k.

In Equation 1, the first term shows the current velocity of the particle, second term presents the cognitive part of PSO where the particle changes its velocity is based on its own thinking and memory. The third term corresponds to the social part of PSO where the particle changes its velocity based on the social-psychological adaptation of knowledge. Each particle moves from the current position to the next one by the updated velocity in Equation 1 as follows:

$$X_i^{k+1}=X_i^k+V_i^{k+1} \quad (2)$$

Suitable chosen of the inertia weight provides a balance between global and local exploration and exploitation, and results in less iteration on average to find a suitably optimal solution. Usually, the linearly decreasing inertia weight factor is used as follows:

$$\omega=\omega_{\max}-\frac{\omega_{\max}-\omega_{\min}}{\mathrm{K}_{\max}}\times\mathrm{k} \quad (3)$$

Where, ω_{max} and ω_{min} are both random numbers called initial weight and final weight, respectively; K_{max} is the maximum iteration number and k is the current iteration number.

PSO-TVAC concept

In the PSO, proper control of the two stochastic acceleration components: the *cognitive* component (c_1) which corresponds to the personal thinking of each particle and the *social* component (c_2) which describes the collaborative effect of the particles, to obtain the global optimal solution is very important accurately and successfully. It should be noted that it is desirable that for cheering the particles to wander through the entire search space, without clustering around local optima during the early stages of the swarm-based optimization (Kuo et al., 2010). On the other hand, in order to find the optimal solution effectively it is very important to enhancement convergence toward the global optima during the latter processes (Boonyaritdachochai et al., 2010). Thus, a novel parameter automation strategy for the PSO concept called PSO with time varying acceleration coefficients is proposed, in this study. The motivation for using this method is enhancement the global search in the early stage of the optimization stages and cheering the particles to converge toward the global optima at the end of it. All parameters including inertia weight and acceleration coefficients are varied with time (iterations) in Equation 1. Thus, in the PSO-TVAC the velocity is updated as follows:

$$\begin{aligned} v_i^{k+1}=C\{&\omega\times v_i^k+[(c_{1f}-c_{1i})\frac{iter}{iter_{\max}}+c_{1i}]\times rand()\times(Pbset_i^k-x_i^k)\\ &+[(c_{2f}-c_{2i})\frac{iter}{iter_{\max}}+c_{2i}]\times rand()\times(Gbset_i^k-x_i^k)\}\end{aligned} \quad (4)$$

$$C=\frac{2}{\left|2-\varphi-\sqrt{\varphi^2-4\varphi}\right|}\quad,\text{where } 4.1\le\varphi\le4.2 \quad (5)$$

Where, C is constriction factor, c_{1i}, c_{1f} and c_{2i}, c_{2f} are initial and final values of c_1 and c_2, respectively. Under this situation, the inertia weight, ω, is linearly decreasing as time grows based on the equation as given in (5) and by changing the acceleration coefficients with time the cognitive component is reduced and the social component is increased (Ratnaweera et al. 2004). The large and small value for cognitive and social component at the optimization process starting is permitted the particles to move around the search space, instead of moving toward the population best. In contrast, using a small and large cognitive and social component, respectively the particles are permitted to converge toward the global optima in the latter part of the optimization. Thus, PSO-TVAC is easier to understand and implement and its parameters have more straight forward effects on the optimization performance in comparison with classic PSO.

Using the above concepts, the whole PSO-TVAC algorithm can be described as follows:

1. For each particle, the position and velocity vectors will be randomly initialized with the same size as the problem dimension within their allowable ranges.
2. Evaluate the fitness of each particle (Pbest) and store the particle with the best fitness (Gbest) value.
3. Update velocity and position vectors according to (4) and (2) for each particle.

Repeat steps 2 and 3 until a termination criterion is satisfied.

Compared the classic PSO, PSO-TVAC has faster convergence and computational efforts. Because can get the quality results in significantly fewer fitness evaluations and constraint evaluations.

The main features of the PSO-TVAC algorithm are robustness to control parameters, easy implementation and high quality solutions. Also, it conducts both global search and local search in each iteration process, and as a result the probability of finding the optimal global solution is significantly increased. Thus, it has a flexible and well-balanced mechanism to enhance the global and local exploration abilities than the classical PSO one and other heuristic techniques.

Problem statement

Power system model

For the stability analysis of power system a sufficient mathematical models involving a set of nonlinear differential-algebraic equations by assembling the models for each generator, load and other devices such as controls in the system is required. The two-axis model (fourth order) (Padiyar, 2008) given in Appendix A is used for the time domain simulations study for each machine.

PSS structure

In this study, a widely used stabilizer with the lead-lag structure based on the speed deviation of the generator is considered for the PSS scheme as follows (Shayeghi et al., 2010; Eslami et al., 2010):

$$U_i = K_i \frac{sT_w}{1+sT_w}\left[\frac{(1+sT_{1i})(1+sT_{3i})}{(1+sT_{2i})(1+sT_{4i})}\right]\Delta\omega_i(s) \qquad (6)$$

Where, $\Delta\omega_i$ is the speed deviation of the ith generator and U_i is the output signal fed as a supplementary input signal to the regulator of the excitation system. This type of PSS consists of a washout filter and a dynamic compensator. The washout filter, which really is a high pass filter, is considered to reset the steady-state offset in the output of the stabilizer. The value of the time constant T_w is usually not critical and it can range from 0.5 to 20 s. Here, it is sited to 10 *s*. The optimized parameters of PSS are:

K_i Gain of PSS

T_{1i}-T_{4i} lead-lag block time constants

PSS design using PSO-TVAC

In this study, the PSS design problem is formulated as an optimization problem and solved by PSO-TVAC 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-TVAC behaviors. For our optimization problem, an Integral of Squared Time multiplied value of the Squared Error (ISTSE) based objective function for multiple operation conditions is considered as follows:

$$F = \sum_{j=1}^{NP}\sum_{i=1}^{NG}\int_0^{tsim} t^2(\Delta\omega_{i,j})^2 dt \qquad (7)$$

Where, t_{sim} is the time range of simulation, *NG* is the number of machines and *NP* is the total number of operating points considered for optimization process. The salient feature of this objective function is that it needs the minimal dynamic plant information. It is aimed to minimize this objective function in order to improve the system response in terms of the settling time and overshoots. The design problem can be formulated as the following constrained optimization problem, where the constraints are the PSS parameters bounds:

$$\begin{aligned}
&Minimize\ \ F\ \ subject\ to\\
&K_i^{\min} \le K_i \le K_i^{\max}\\
&T_{1i}^{\min} \le T_{1i} \le T_{1i}^{\max}\\
&T_{2i}^{\min} \le T_{2i} \le T_{2i}^{\max}\\
&T_{3i}^{\min} \le T_{3i} \le T_{3i}^{\max}\\
&T_{4i}^{\min} \le T_{4i} \le T_{4i}^{\max}
\end{aligned} \qquad (8)$$

The proposed approach employs PSO-TVAC to solve this optimization problem and search for the optimal set of PSSs parameters. Robustness is verified by considering numerous operating conditions and the system configurations, simultaneously.

RESULTS

The IEEE three-machine nine-bus power system shown in Figure 1 is considered as a test system in this work. The required system data are given in (Anderson and Fouad, 1979). To evaluate the efficacy and robustness of the proposed optimization technique over a wide range of loading conditions, four different cases designated as nominal, lightly, heavily and other loading conditions are considered, where the generator and system loading levels at these cases are given in Tables 1 and 2.

In the test system, G_2 and G_3 machines are equipped to the PSS. In the proposed control scheme, we must tune the parameters of the PSSs, optimally to enhance the overall system dynamic stability, in a robust way under several operating conditions and disturbances. The optimal tuning of the PSS parameters is carried out by evaluating the fitness function as given in Equation 8 for four operating conditions as given in Table 2 by applying a 6-cycle three-phase fault at *t*=1 s, at bus 7 at the end of line 5-7. The fault is cleared by stable tripping of the faulted line. In this study, the PSO module works offline. For the each PSS, the optimal setting of five parameters is determined by the PSO-TVAC, that is, 10 parameters

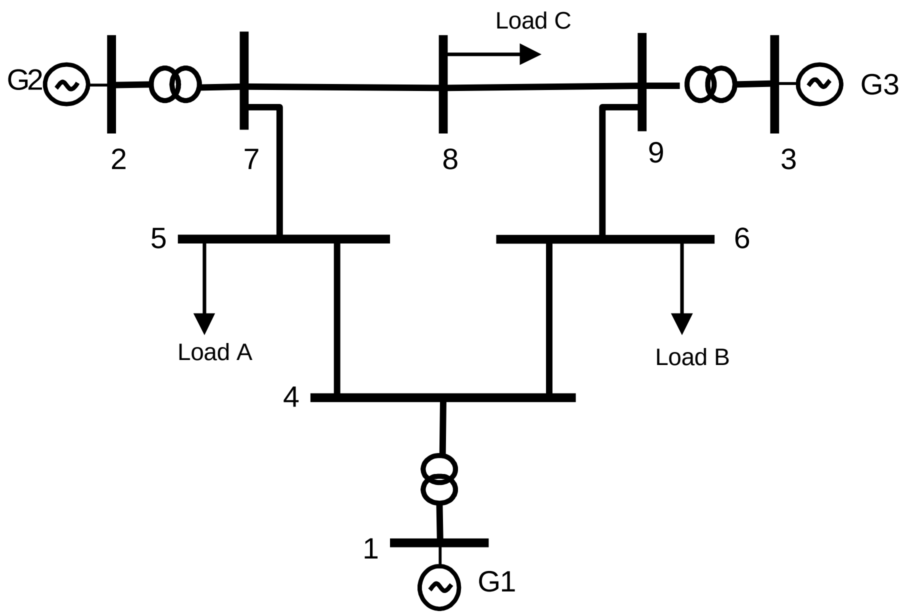

Figure 1. Three-machine nine-bus power system.

Table 1. Generator operating conditions (in pu).

Gen	Nominal		Heavy		Light		Other load		V_t (pu)
	P(pu)	Q(pu)	P(pu)	Q(pu)	P(pu)	Q(pu)	P(pu)	Q(pu)	
G_1	0.72	0.27	2.21	1.09	0.36	0.16	0.33	1.12	1.040
G_2	1.63	0.07	1.92	0.56	0.80	-0.11	2.00	0.57	1.025
G_3	0.85	-0.11	1.28	0.36	0.45	-0.20	1.50	0.38	1.025

Table 2. Loading conditions (in Pu).

Bus	Nominal		Heavy		Light		Other load	
	P(pu)	Q(pu)	P(pu)	Q(pu)	P(pu)	Q(pu)	P(pu)	Q(pu)
5	1.25	0.5	2.0	0.80	0.65	0.55	1.50	0.90
6	0.90	0.30	1.80	0.60	0.45	0.35	1.20	0.80
8	1.0	0.35	1.50	0.60	0.50	0.25	1.00	0.50

Table 3. PSO-TVAC and PSO parameters for optimization.

PSO-TVAC		PSO	
C_{1f}	0.2	C_1	2.1
C_{1i}	2.5	C_2	2.1
C_{2f}	2.5	ω_{min}	0.4
C_{2i}	0.2	ω_{max}	0.9
φ	4.1	Population	40
ω_{min}	0.4	Iteration	100
ω_{max}	0.9	-	-
Population	40	-	-
Iteration	100	-	-

to be optimized, namely K_i, T_{1i}-T_{4i} for $i= 2, 3$. In order to facilitate comparison with the classical PSO and conventional approaches, the design and tuning of the PSS parameters for this multi-machine power system, the phase compensation (Larsen and Swann, 1981) and PSO methods (Shayeghi et al., 2010) were used. In order to acquire better performance, the control parameters of the proposed PSO-TVAC and classical PSO algorithm is given in Table 3. Optimized PSSs parameter set values according to the objective function as given in Equation 8 using the above methods are listed in Table 4. Figure 2 shows the minimum fitness functions evaluating process.

Table 4. Optimal PSSs parameters.

Method	Gen	K_{pss}	T_1	T_2	T_3	T_4
CPSS	G_2	2.4172	0.2709	0.0483	0.2709	0.0483
	G_3	1.7344	0.1910	0.0340	0.1910	0.0340
CPSO	G_2	13.4300	0.2521	0.0570	0.4633	0.0538
	G_3	3.7400	0.6135	0.0311	0.4249	0.0964
PSO-TVAC	G_2	17.6750	0.8201	0.0478	0.1101	0.0667
	G_3	7.9800	0.9002	0.0403	0.1204	0.0663

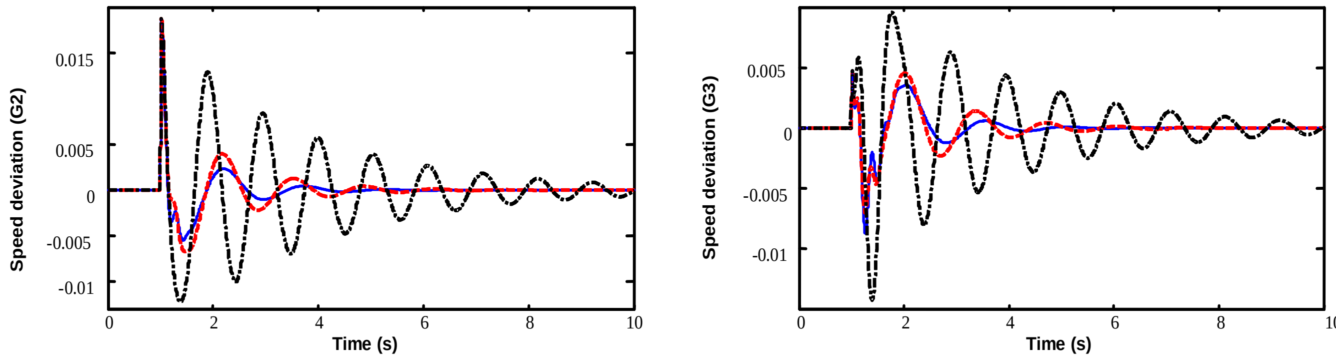

Figure 2. System response under nominal loading in scenario 1; Solid (PSO-TVAC), Dashed (PSO) and Dotted (CPSS).

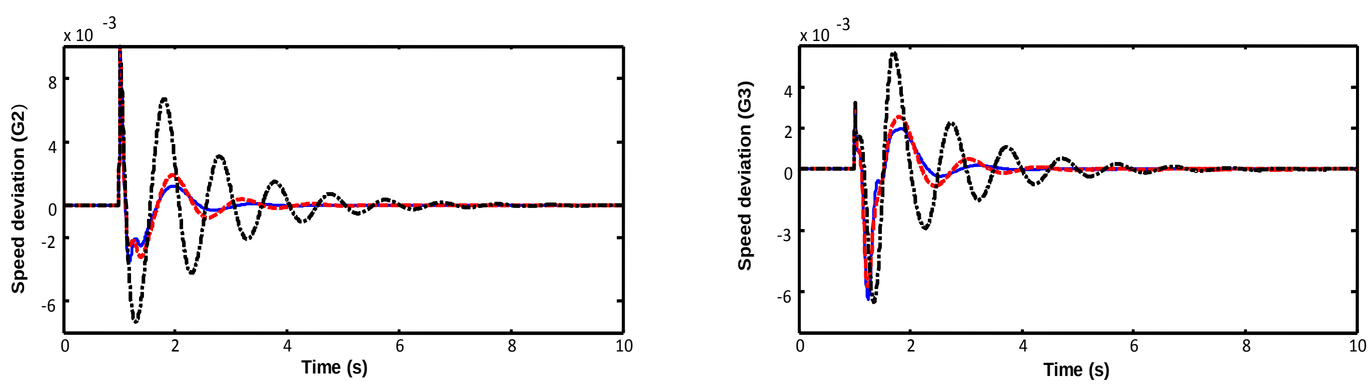

Figure 3. System response under lightly loading in scenario 1; Solid (PSO-TVAC), Dashed (PSO) and Dotted (CPSS).

Nonlinear time-domain simulation

The effectiveness and robustness of the proposed PSO-TVAC based designed PSS for different operating conditions as given in Table 2 and fault disturbances is demonstrated through the nonlinear time simulation and some performance indices in comparison to that of the PSSs tuned using the PSO and CPSS (Larsen and Swann, 1981) methods for two scenarios.

Scenario 1

In this scenario, the effectiveness of the proposed stabilizer under transient conditions is verified by applying a six-cycle three-phase fault at *t*=1 s, at bus 7 at the end of line 5-7. The fault is cleared without line tripping and the original system is restored upon the clearance of the fault. The speed deviations of generators G_2 and G_3 under different loading conditions are shown in Figures 2

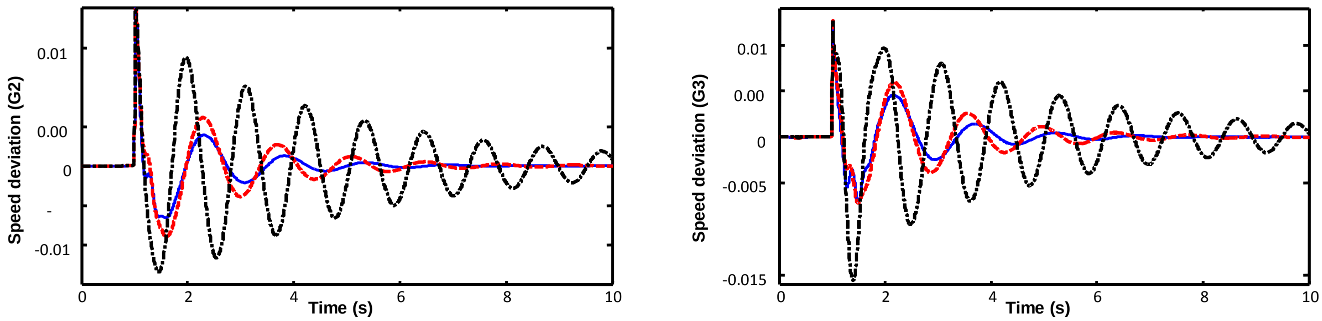

Figure 4. System response under heavily loading in scenario 1; Solid (PSO-TVAC), Dashed (PSO) and Dotted (CPSS).

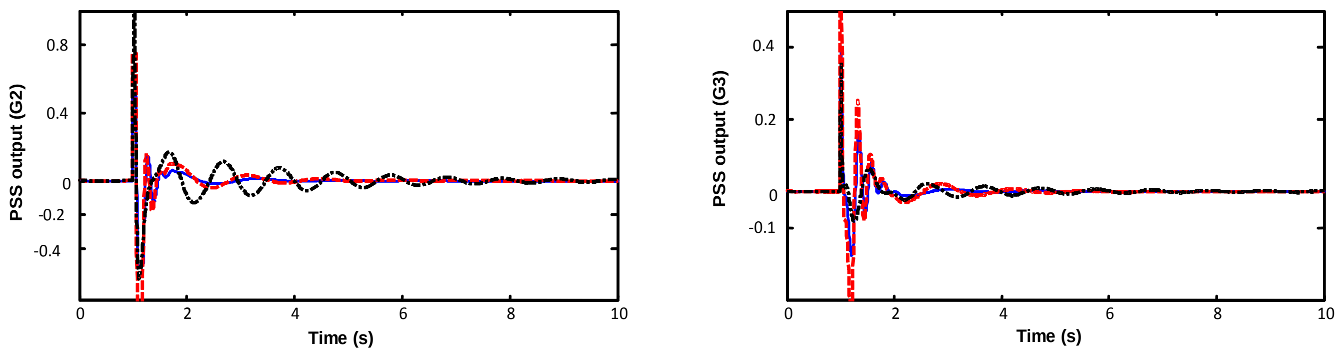

Figure 5. Stabilizing signals at generators G_2 and G_3 under nominal loading; Solid (PSO-TVAC), Dashed (PSO) and Dotted (CPSS).

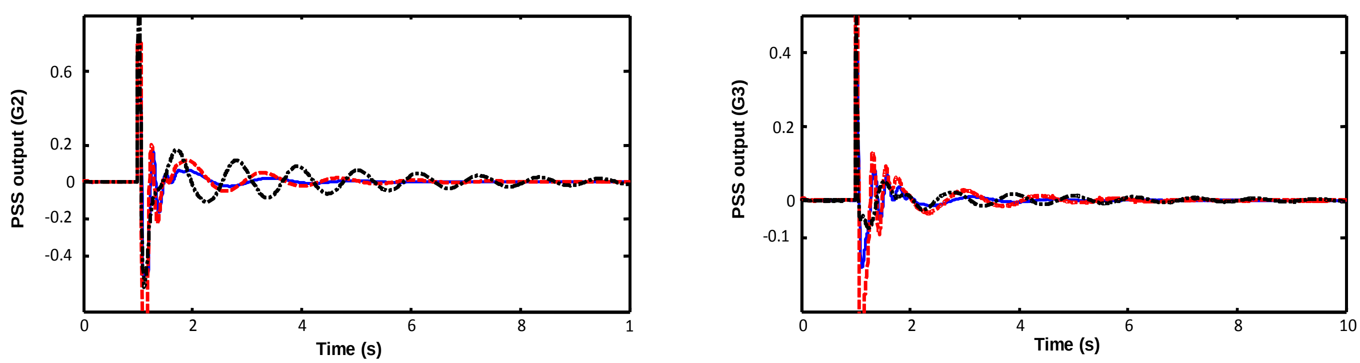

Figure 6. Stabilizing signals at generators G_2 and G_3 under heavy loading; Solid (PSO-TVAC), Dashed (PSO) and Dotted (CPSS).

and 4. It can be seen that the proposed stabilizer achieves good robust performance and provides superior damping in comparison with the conventional and PSO methods. For completeness, the stabilizing signals for the stabilizers of generators G_2 and G_3 are shown in Figures 5 and 6. It can be concluded that the optimized stabilizer using PSO-TVAC technique provides much proper control signals than the PSO and classical methods based designed PSSs.

Scenario 2

In this scenario, another hybrid severe disturbance is considered for different loading conditions; that is, a 0.1 p.u. step increase in mechanical torque of all generators was applied at t=0.5 s and after a few seconds a 6-cycle three-phase fault at t=5 s, on bus 7 at the end of line 5-7 for the system will be applied. The fault is cleared by stable tripping of the faulted line. The speed deviations of

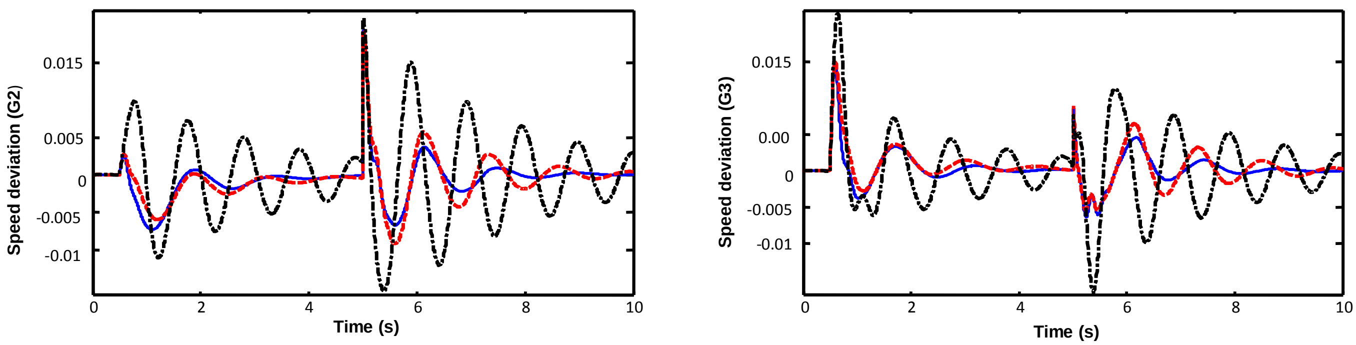

Figure 7. System response under nominal loading in scenario 2; Solid (PSO-TVAC), Dashed (PSO) and Dotted (CPSS).

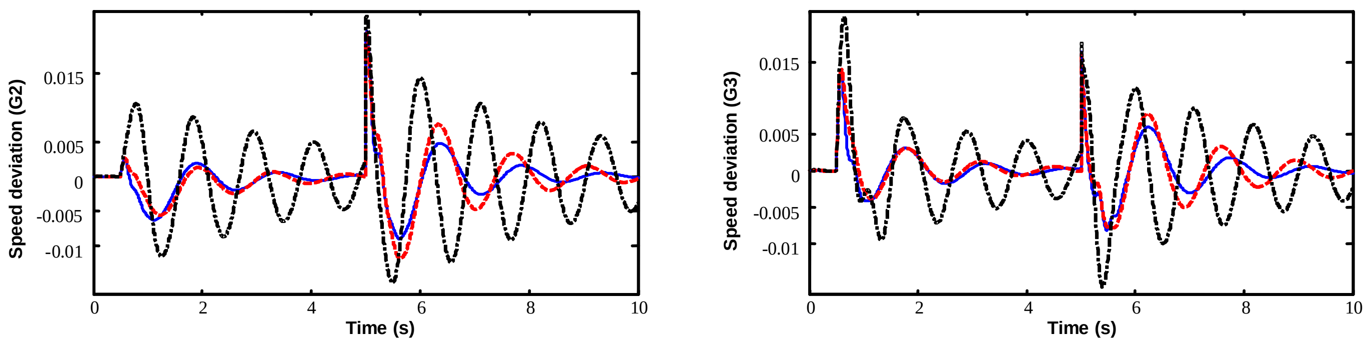

Figure 8. System response under heavily loading in scenario 2; Solid (PSO-TVAC), Dashed (PSO) and Dotted (CPSS).

all generators under the nominal and heavily loading conditions are shown in Figures 7 and 8. Using the proposed method, the speed deviation of both generators is quickly driven back to zero and have small settling time. Moreover, it can be seen that the proposed ABCPSS achieves good robust performance and provides superior damping in comparison with other PSSs.

DISCUSSION

In order to have a fair comparison in terms of solution quality and computation efficacy among the CPSO, and PSO-TVAC methods, each algorithm is run for 10 trials and the best fitness value is shown in Figure 9. It is evident that using PSO-TVAC for optimal tuning of PSSs has faster convergence rate compared to CPSO one.To illustrate robustness of the proposed method, two performance indices: the Figure of Demerit (FD) and Integral of the Time multiplied Absolute value of the Error (ITAE) based on the system performance characteristics are defined as:

$$ISE = 10000 \int_0^{t_{sim}} (\omega_1^2 + \omega_2^2 + \omega_3^2).dt \qquad (9)$$

$$IAE = 1000 \int_0^{t_{sim}} (|\omega_1| + |\omega_2| + |\omega_3|).dt \qquad (10)$$

$$ITAE = 1000 \int_0^{t_{sim}} t\,(|\omega_1| + |\omega_2| + |\omega_3|).dt \qquad (11)$$

$$FD = \frac{\sum_{i=1}^{N_G} ((350 \times OS_i)^2 + (600 \times US_i)^2 + T_{s,i}^2)}{N_G} \qquad (12)$$

Where, OS_i, US_i and T_{si} are overshoot, undershoot and settling time of rotor angle deviation of *i*th machine is considered. It is merit mentioning that the lower the value of these indices is, the better the system response in terms of the time-domain characteristics. The values of the above performance indices are calculated under the two above scenarios, whereas the system load are varied from -25 to 25% of the nominal loading condition. Numerical results are shown the in Tables 5 to 6 for different operation conditions with three stabilizers under scenarios 1 and 2. Assessment of these Tables reveals that the using the proposed PSO-TVAC the speed deviations of all machines are greatly reduced, has small overshoot, undershoot and settling time. Moreover, it

Table 5. Values of the performance indices under scenario 1.

Load change percentage	PSO-TVAC				CPSO				CPSS			
	ITAE	FD	IAE	ISE	ITAE	FD	IAE	ISE	ITAE	FD	IAE	ISE
25	24.5029	40.132	12.9076	0.5017	36.0923	47.378	16.6556	0.6152	143.3280	86.265	47.4541	2.4495
20	24.7673	42.172	13.0413	0.5138	37.1454	49.261	17.0570	0.6399	153.3448	89.019	49.6985	2.5951
15	25.0319	43.254	13.1673	0.5257	37.9202	51.763	17.3095	0.6535	164.9099	91.276	52.2103	2.7562
10	25.2866	46.234	13.2926	0.5368	39.1475	54.829	17.7587	0.6798	178.3591	93.827	55.0673	2.9433
5	25.5536	48.524	13.4252	0.5484	40.3253	57.982	18.1660	0.7021	194.1621	95.209	58.3237	3.1579
Nominal	25.9648	49.321	13.6223	0.5648	41.5147	61.001	18.5678	0.7234	212.5771	97.389	61.9803	3.3984
-5	26.2690	52.817	13.7871	0.5765	42.7899	63.726	18.9900	0.7427	234.8882	99.245	66.3703	3.7004
-10	26.6858	55.387	13.9766	0.5928	44.6139	65.721	19.6061	0.7774	261.4396	101.99	71.3548	4.0477
-15	27.1446	59.276	14.1814	0.6096	46.3975	67.905	20.1638	0.8061	293.3224	106.27	77.1769	4.4683
-20	27.6007	62.716	14.3795	0.6258	48.3569	69.162	20.7736	0.8370	332.0873	109.24	84.0432	4.9886
-25	27.8685	65.817	14.4801	0.6342	50.2616	70.451	21.3077	0.8598	379.2600	113.27	92.1666	5.6431

Table 6. Values of the performance indices under scenario 2.

Load change percentage	PSO-TVAC				CPSO				Classic			
	ITAE	FD	IAE	ISE	ITAE	FD	IAE	ISE	ITAE	FD	IAE	ISE
25	113.4688	71.928	29.4275	1.2150	152.4141	97.356	35.4404	1.4785	389.9191	130.278	83.6959	5.0739
20	115.0055	75.273	29.8950	1.2468	155.5674	99.167	36.1104	1.5159	409.4241	135.722	87.0249	5.3575
15	116.7365	78.265	30.4129	1.2818	161.4932	102.18	37.1869	1.5696	431.4883	139.672	90.7793	5.6884
10	118.9032	79.287	31.0005	1.3176	169.8427	105.28	38.6024	1.6339	456.5247	142.019	95.0214	6.0764
5	123.5589	81.203	31.9580	1.3657	180.4081	109.56	40.3273	1.7138	485.0056	144.266	99.8213	6.5342
Nominal	130.2484	83.387	33.2257	1.4231	200.2210	112.81	43.2169	1.8223	518.1693	147.256	105.437	7.0985
-5	146.0400	87.256	35.5720	1.4933	234.9517	115.37	47.8688	2.0049	555.5162	150.245	111.659	7.7538
-10	167.4788	90.178	38.7365	1.6236	274.0150	117.98	53.0097	2.2363	598.0119	153.090	118.647	8.5297
-15	184.8617	93.109	41.3652	1.7668	313.0262	119.65	58.4584	2.6056	647.4693	159.162	126.771	9.4924
-20	206.2730	95.387	44.9148	1.9236	337.1773	121.26	61.9475	2.8257	705.6064	164.156	136.325	10.706
-25	230.8144	97.283	48.9843	2.1596	377.4379	127.61	67.5835	3.2822	771.5131	166.928	146.959	12.158

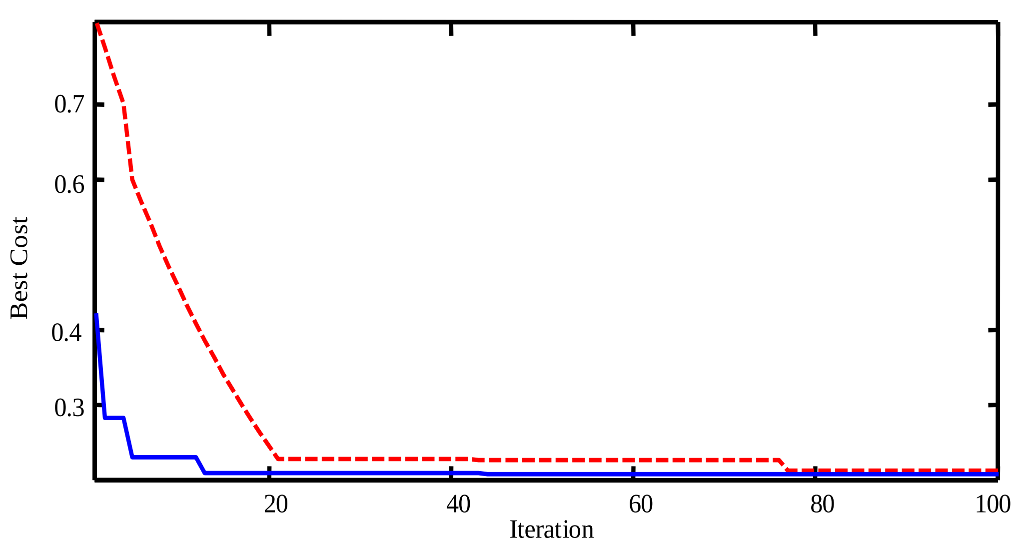

Figure 9. Convergence of fitness functions; Dashed (PSO) and Solid (PSO-TVAC).

achieves good robust performance compared to that of PSO and classical methods designed PSSs.

Conclusions

In this paper, the improved PSO with time-varying acceleration coefficients algorithm has been proposed to optimal tune of the PSS parameters to enhance the relative stability and secure operation of the multi machine power systems. To optimize the parameters of the stabilizers a time domain-based objective for a wide range of operation conditions is introduced and solved by PSO-TVAC. It performs both global and local search at each iteration process for significant increasing the probability of finding the optimal solution. Hence, the convergence precision and speed are remarkably improved and then the high precision and efficiency are achieved.

The effectiveness of the proposed PSO-TVAC based tuned PSSs is shown on a multi-machine power system in comparison with the classical PSO and conventional method based designed PSSs through the nonlinear time domain simulation and some performance indices for a wide range of loading condition. The non-linear time domain simulation results show the improved PSO-TVAC algorithm provides good ability for effectively damping low frequency oscillations.

Moreover, the system characteristics analysis using different introduced performance indices reveal that the proposed PSO-TVAC algorithm is superior that of the classical PSO one in terms of accuracy, convergence and computational effort.

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