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APPLICATION OF PSO-TVAC TO IMPROVE LOW FREQUENCY OSCILLATIONS

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Abstract- A Particle Swarm Optimization with Time-Varying Acceleration Coefficients (PSO-TVAC) algorithm is proposed to design of the Power System Stabilizer (PSS) for improvement of power system low frequency oscillations in this paper. It has a strong ability to successful control the local search and convergence to the global optimum solution. The problem of robustly PSS parameter tuning is formulated as an optimization problem according to the time domain-based objective function for a wide range of operating conditions and is solved by the PSO-TVAC technique which is simple, robust and capable to solve difficult combinatorial optimization problems. The effectivness of the proposed method is tested on a Single-Machine Infinite-Bus (SMIB) power system through the nonlinear time domain simulation and some performance indices in comparison with the other version of PSO based tuned stabilizer and conventional PSS to illustrate its robust performance. Results evaluation confirm that the proposed stabilizer achieves good robust performance for wide range of system operation conditions and is superior to the other PSSs.

Keywords: PSS Design, PSO-TVAC Algorithm, Low Frequency Oscillations, SMIB.

I. INTRODUCTION

The dynamic stability of power systems is an important factor for secure system operation. By the development of interconnection of large electric power systems, there have been spontaneous system oscillations at very low frequencies in order of 0.2-3.0 Hz [1]. 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 provides supplementary feedback stabilizing signals in the excitation system.

The action of a Power System Stabilizer (PSS) is to extend the angular stability limits of a power system by providing supplemental damping to the oscillation of the synchronous machine rotors through the generator excitation. This damping is provided by an electric torque applied to the rotor that is in phase with the speed variation. Power system instabilities can arise in certain circumstances due to the negative damping effects of the PSS on the rotor, which is based on tuning PSSs around a steady-state operating point; their damping effect is only valid for the small excursions around this operating point. During severe disturbances, a PSS may actually cause the generator under its control to loose synchronism in an attempt to control its excitation field [2].

A number of the conventional techniques have been reported in the literature pertaining to design widely used conventional lead-lag compensator based PSS namely: the eigenvalue assignment, mathematical programming, gradient procedure for optimization and also the modern control theory [2-5]. Unfortunately, the conventional techniques are time consuming as they are iterative and require heavy computation burden and slow convergence. In addition, the search process is susceptible to be trapped in local minima and the solution obtained may not be optimal [4]. Also, a set of controller parameters which stabilize the system under a certain operating condition may no longer yield satisfactory results when there is a drastic change in power system operating conditions and configurations [5].

A more reasonable design of the PSS is based on the gain scheduling and adaptive control theory as it takes into consideration the nonlinear and stochastic characteristics of the power systems [6-7]. This type of stabilizer can adjust its parameters on-line according to the operating condition. Many years of intensive studies have shown that the adaptive stabilizer can not only provide good damping over a wide operating range but more importantly, it can also solve the coordination problem among the stabilizers. Many random heuristic methods, such as like Tabu search, genetic algorithms, chaotic optimization algorithm and rule based bacteria foraging have recently received much interest for achieving high efficiency and search global optimal solution in the problem space and they have been applied to optimal tune of the lead-lag compensator based PSS parameters [8-11]. These evolutionary based methods are heuristic population-based search procedures that incorporate random variation and selection operators.

Although, these methods seem to be good approaches for the solution of the PSS parameter optimization problem, however, when the system has a highly epistatic objective function (i.e. where parameters being optimized are highly correlated), and number of parameters to be optimized is large, then they have degraded effectiveness to obtain the global optimum solution. Recently, the particle swarm optimization (PSO) technique is used for the optimal design of PSS [11]. However, the effectiveness of the classical PSO greatly depends on its parameters, and it often suffers the problem of being trapped in the local optima so as to be premature convergence. In order to overcome these drawbacks, a new parameter automation strategy for PSO algorithm called PSO with time-varying acceleration coefficients (PSO-TVAC) technique is developed and proposed for optimal tune of PSS parameters to improve power system low frequency oscillations damping in this paper. Hence, to improve optimization process in the PSO, the concept of time-varying acceleration coefficients are developed in addition to the time-varying inertia weight factor to efficiently control the local search and convergence to the global optimum solution [12]. The main advantage of the PSO-TVAC algorithm is simple concept, easy implementation, robustness to control parameters and computational effort.

To illustrate the robustness of the proposed PSS and their ability to provide efficient damping of low frequency oscillations it is tested on a weakly connected power system for a wide range of operating conditions. To show the superiority of the proposed design approach, the simulations results are compared with the PSO based designed and classical PSS through nonlinear simulation results and some performance indices. The results evaluation reveals that the proposed PSO-TVAC based tuned PSS achieves good robust performance for wide range of load changes in the presence of very highly disturbance and is superior to the other stabilizers.

II. POWER SYSTEM DESCRIPTION

Figure 1 shows a schematic diagram of a Single Machine connected to an Infinite Bus (SMIB) power system through a circuit transmission. The generator is equipped with excitation system and a power system stabilizer. System data are given in Appendix.

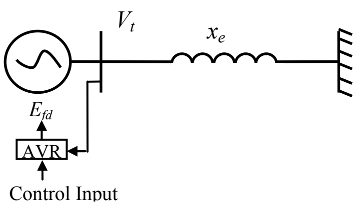

Figure 1. SMIB power system

The model 1.1, i.e. with field circuit and one equivalent damper winding on q axis is used to describe synchronous generator. The dynamic equations of the SMIB system considered can be summarized as [13, 11].

$$\begin{cases} \dot{\delta} = \omega_B S_m \\ \dfrac{dS_m}{dt} = \dfrac{1}{2H}(-DS_m + T_m - T_e) \\ \dot{E}'_q = \dfrac{1}{T'_{do}}(E_{fd} + (x_d - x'_d)i_d - E'_q) \\ \dot{E}_{fd} = \dfrac{1}{T_A}(k_A(v_{ref} - v_t + V_s)) - E_{fd}) \end{cases} \quad (1)$$

$$T_e = E'_q i_q + (x'_d - x'_q)i_d i_q \quad (2)$$

The structure of PSS, to modulate the excitation voltage is shown in Figure 2. The structure consists a gain block with gain K, a signal washout block and two-stage phase compensation blocks. The input signal of the proposed method is the speed deviation ($\Delta\omega$) and the output is the stabilizing signal V_S which is added to the reference excitation system voltage. The signal washout block serves as a high-pass filter, with the time constant T_W, high enough to allow signals associated with oscillations in input signal to pass unchanged. From the viewpoint of the washout function, the value of T_W is not critical and may be in the range of 1 to 20 seconds [11]. The phase compensation block (time constants T_1, T_2 and T_3, T_4) provides the appropriate phase-lead characteristics to compensate for the phase lag between input and the output signals.

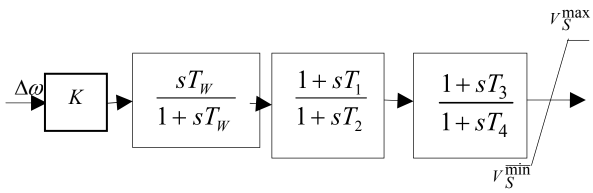

Figure 2. Structure of power system stabilizer

III. PSO-TVAC

A. Standard PSO

Kennedy and Eberhart [14] 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 (e.g., 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.

In a physical-dimensional search space, the position and velocity of individual i are represented as the vectors $X_i = (x_{i1},...,x_{in})$ and $V_i = (v_{i1},...,v_{in})$ in the PSO algorithm, respectively. Let $Pbest_i = \left(x_{i1}^{Pbest},...,x_{in}^{Pbest}\right)$ and $Gbest_i = \left(x_{i1}^{Gbest},..,x_{in}^{Gbest}\right)$ be the best position of particle i and its neighbors’ best position so far. Using this information, the updated velocity of particle is modified as follows:

$$V_i^{k+1} = \omega V_i^k + c_1 rand_1 \times \left(Pbest_i^k - X_i^k\right) + \\ + c_2 rand_2 \left(Gbest^k - X_i^k\right) \qquad (3)$$

where, V_i^k is velocity of particle at iteration k; ω is weight parameter; c_1 and c_2 are weight 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 (3) 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 modified velocity in (3) as follows:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \qquad (4)$$

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. The linearly decreasing inertia weight factor is used as follows:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \qquad (5)$$

where, $w_{\max}$ and $w_{\min}$ are both random numbers called initial weight and final weight, respectively; $iter_{\max}$ is the maximum iteration number and $iter$ is the current iteration number.

B. 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. 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 [15]. Thus, a novel parameter automation strategy for the PSO concept called PSO with time varying acceleration coefficients is proposed, in this paper. 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 (3). Thus, in the PSO-TVAC the velocity is updated as follows:

$$v_i^{k+1} = C\{w \times v_i^k + [(c_{1f} - c_{1i})\frac{iter}{iter_{\max}} + c_{1i}] \times \\ \times rand(\,) \times (Pbset_i^k - x_i^k) + \\ + [(c_{2f} - c_{2i})\frac{iter}{iter_{\max}} + c_{2i}] \times rand(\,) \times (Gbset_i^k - x_i^k)\} \qquad (6)$$

$$w = (w_{\max} - w_{\min}).\frac{w_{\max} - iter}{iter_{\max}} + w_{\min} \qquad (7)$$

$$C = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}\ \text{, where } 4.1 \le \varphi \le 4.2 \qquad (8)$$

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 is linearly decreasing as time grows and by changing the acceleration coefficients with time the cognitive component is reduced and the social component is increased [12]. 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 straightforward effects on the optimization performance in comparison with classic PSO.

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

- For each particle, the position and velocity vectors will be randomly initialized with the same size as the problem dimension within their allowable ranges.
- Evaluate the fitness of each particle (*Pbest*) and store the particle with the best fitness (*Gbest*) value.
- Update velocity and position vectors according to (6) and (4) for each particle.
- Repeat steps 2 and 3 until a termination criterion is satisfied.

Comparing the classic PSO, PSO-TVAC has the following advantages:

i) *Faster*: PSO-TVAC can get the quality results in significantly fewer fitness evaluations and constraint evaluations.

ii) *Cheaper*: There is need to adjust a few parameter settings for different problems than the PSO.

IV. PSO-TVAC BASED PSS DESIGN

For the PSS structure shown in Figure 2, the washout time constants is usually specified. In this study, washout time constant, T_W is set 10 s. The PSS gain, K, and the time constants T_1, T_2, T_3 and T_4 are to be optimized. It is worth mentioning that the PSS parameters are tuned to minimize the power system oscillations after a large disturbance so as to improve the power system stability. These oscillations are reflected in the deviations of the power angle, rotor speed and line power. Minimization of any one or all of the above deviations could be selected as the objective function (fitness).

Here, an Integral of the Squared Time of the Squared Error (ISTSE) of the speed deviations is taken as the objective function is given by:

$$F = \sum_{i=1}^{NP} \int_{t=0}^{t=tsim} t^2 (\Delta\omega)^2 \, dt \quad (9)$$

where, $\Delta\omega$ shows the rotor speed deviation for a set of PSS parameters, t_{sim} is the time range of the simulation and NP is the total number of operating conditions for which the optimization is carried out. It is aimed to minimize this objective function in order to enhancement the system response in terms of the settling time and overshoots under different operating condition. The PSS design problem can be formulated as the following constrained optimization problem, where the constraints are the stabilizers bounds [9, 11]:

minimize F subject to:

$$\begin{aligned} &K^{\min} \le K \le K^{\max} \\ &T_1^{\min} \le T_1 \le T_1^{\max} \\ &T_2^{\min} \le T_2 \le T_2^{\max} \\ &T_3^{\min} \le T_3 \le T_3^{\max} \\ &T_4^{\min} \le T_4 \le T_4^{\max} \end{aligned} \quad (10)$$

Typical ranges of the optimized parameters are [0.01-50] for K and [0.01-1] for T_1, T_2, T_3 and T_4. The proposed method employs PSO-TVAC algorithm to solve this optimization problem and search for an optimal or near optimal set of PSS parameters. The optimization of the PSS parameters is carried out by evaluating the objective cost function as given in Equation (10), which considers a multiple of operating conditions are given in Table 1.

The operating conditions are considered for wide range of output power at different power factors. To acquire better optimization synthesis, the PSO-TVAC and classical PSO parameters is given in Table 2. Results of the PSS parameter set values based on the objective function F, by applying a three phase-to-ground fault for 100 ms at generator terminal at t=1 sec using the proposed PSO-TVAC and classical PSO algorithms [9] are given in Table 3. The Classical PSS (CPSS) is design using the tuning guidelines given in [13] for nominal operating point. Figure 3 shows the minimum fitness functions evaluating process.

Table 1. Operation conditions

Case No.	P	Q	x_e	H
Case 1 (base case)	0.8	0.4	0.3	3.25
Case 2	0.5	0.1	0.3	3.25
Case 3	1	0.5	0.3	3.25
Case 4	0.8	0.4	0.6	3.25
Case 5	0.5	0.1	0.6	3.25
Case 6	1	0.5	0.6	3.25
Case 7	0.8	0	0.6	3.25
Case 8	1	-0.2	0.3	3.25
Case 9	0.5	-0.2	0.6	3.25
Case 10	1	0.2	0.3	0.81

V. SIMULATION RESULTS

The performance of the proposed PSO-TVAC based designed PSS under transient conditions is verified by applying disturbance and fault clearing sequence under different operating conditions in comparison with the PSO based tuned PSS (PSOPSS) and classical PSS (CPSS). The disturbances are given at t=1 sec. System responses in the form of slip (S_m) are plotted. The following types of disturbances have been considered.

Scenario 1: Applying a step change of 0.1 pu in the input mechanical torque of the generator.

Scenario 2: Applying a three phase-to-ground fault for 100 ms at the generator terminal.

Scenario 3: Applying a three phase-to-ground fault for 100 ms at the generator terminal at t=1 sec and a step change of 0.1 pu in the input mechanical torque of the generator at t=5 sec.

Table 2. 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	$w_{\min}$	0.4
C_{2i}	0.2	$w_{\max}$	0.9
φ	4.1	Population	40
$w_{\min}$	0.4	Iteration	100
$w_{\max}$	0.9	-	-
Population	40	-	-
Iteration	100	-	-

Table 3. Optimal PSS parameters

Method	K_{pss}	T_1	T_2	T_3	T_4
CPSS	12.5	0.0738	0.0280	0.0738	0.0280
PSO	13.0100	0.0930	0.0091	0.0820	0.0111
PSO-TVAC	25.5600	0.0980	0.0195	0.0883	0.0103

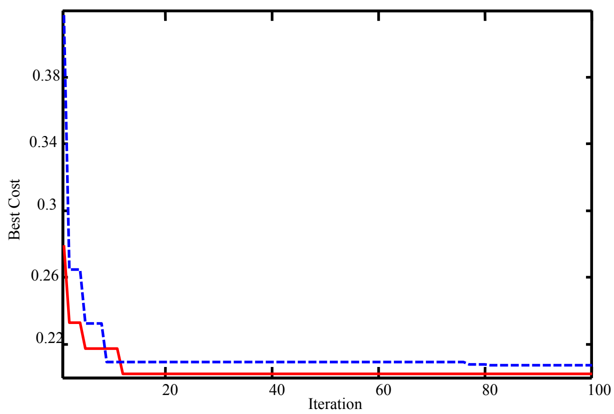

Figure 3. Fitness convergence, Dashed (PSO) and Solid (PSO-TVAC)

Figure 4 depicts the system response at the lagging power factor operating conditions with weak transmission system for scenario 1. It is clear that the system with CPSS is highly oscillatory. Both PSO-TVAC and PSO based tuned stabilizers are able to damp the oscillations reasonably well and stabilize the system at all operating conditions. Figure 5 shows the responses of same operating conditions but with strong transmission system. System is more stable in this case, following any disturbance. Both PSS improve its dynamic stability considerably and PSO-TVAC based PSS shows its superiority over PSOPSS and CPSS. System response at the ohmic operating conditions is shown in Figure 6 with the weak and strong transmission system for scenario 1. The proposed PSO-TVAC based PSS is effective and achieves good system damping characteristics.

Also, Figure 7 show the system response at the leading power factor operating conditions with the weak and strong transmission system for scenario 1. Figure 8 refers to a three-phase to ground fault at the generator terminal. Figure 9 depicts the system response in scenario 1 with inertia $H' = H/4$. It can be seen that the proposed ABC based PSS has good performance in damping low frequency oscillations and stabilizes the system quickly. Moreover, it is superior to the PSO and classical based methods tuned stabilizer.

The system response using the proposed PSS in scenario 3 for operation conditions of cases 1, 7, 8 and 10 is depicted in Figure 10. It is evident that the system low frequency osillation damping using the proposed PSO-TVAC tuned PSS has small overshoot, less setteling time and is seprior that of the other approaches one.

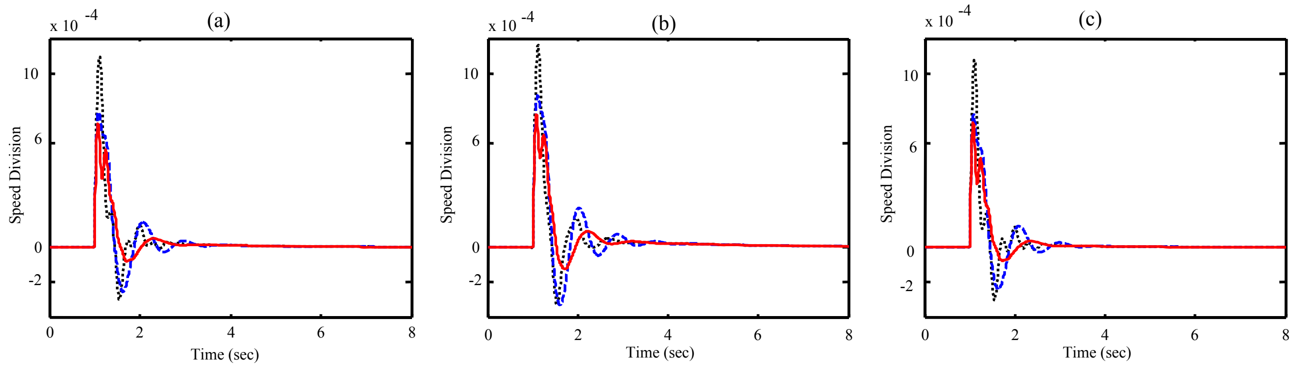

Figure 4. ΔT_m=0.1 (p.u.) under X_e=0.3; CPSS (Dotted), PSOPSS (Dashed) and PSO-TVACPSS (Solid)
(a) P=0.8, Q=0.4 (b) P=0.5, Q=0.1 (c) P=1.0, Q=0.5

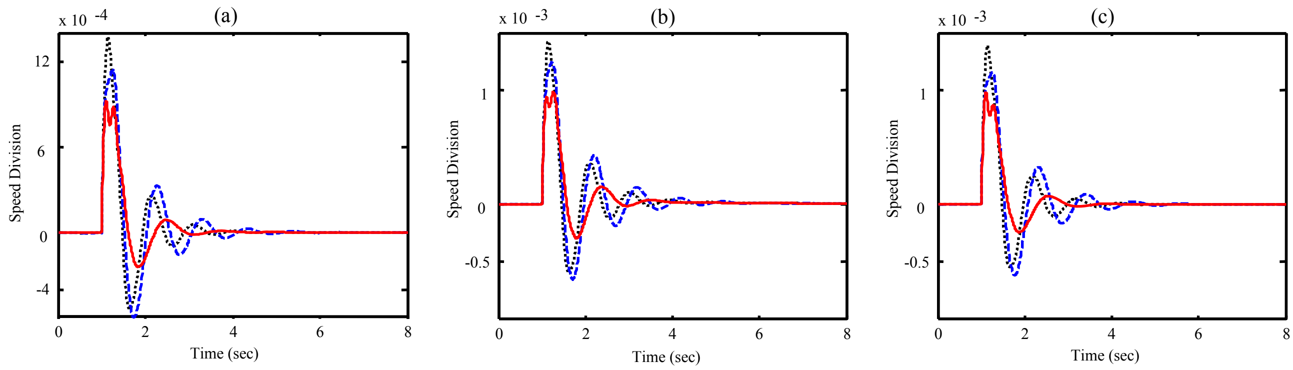

Figure 5. ΔT_m=0.1 (p.u.) under X_e=0.6; CPSS (Dotted), PSOPSS (Dashed) and PSO-TVACPSS (Solid)
(a) P=0.8, Q=0.4 (b) P=0.5, Q=0.1 (c) P=1.0, Q=0.5

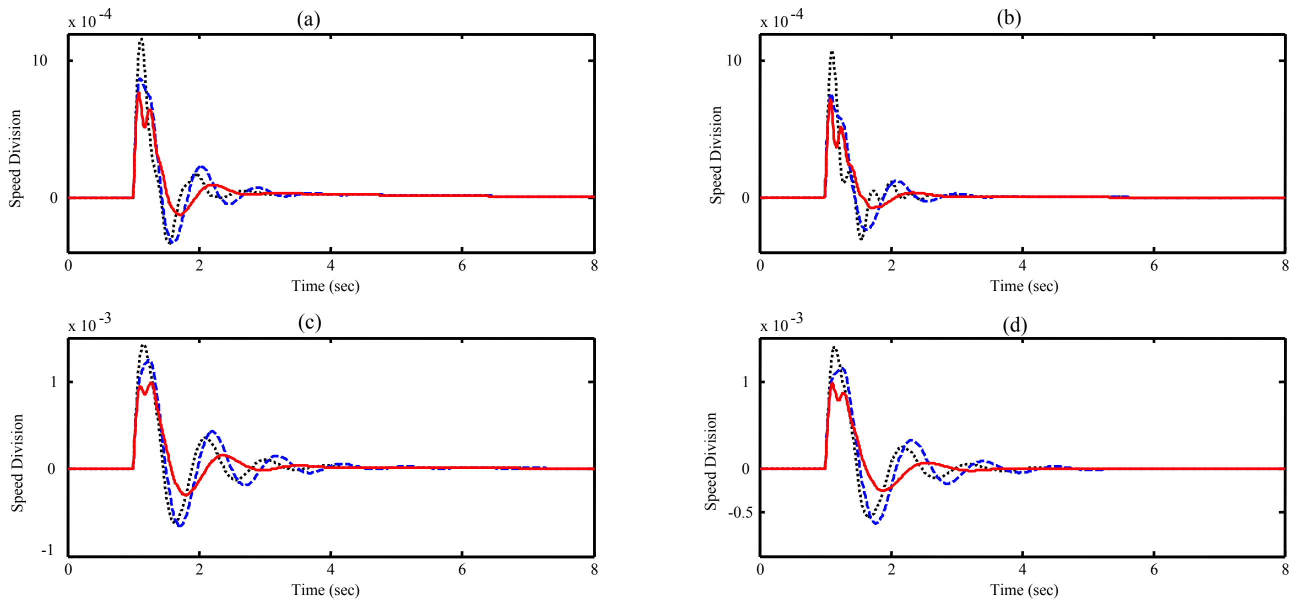

Figure 6. ΔT_m=0.1 (p.u.); CPSS (Dotted), PSOPSS (Dashed) and PSO-TVACPSS (Solid)
(a) P=0.5, Q=0.0, X_e=0.3 (b) P=1.0, Q=0, X_e=0.3 (c) P=0.5, Q=0.0, X_e=0.6 (d) P=1.0, Q=0, X_e=0.6

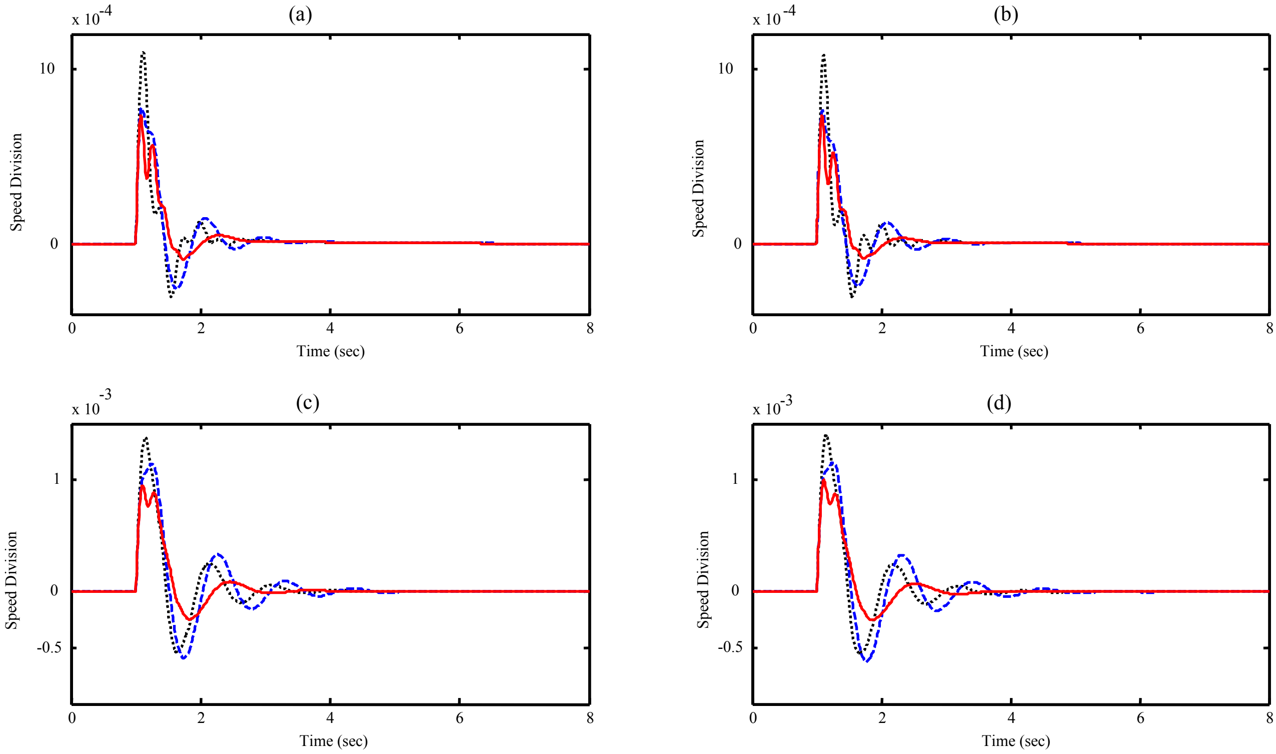

Figure 7. ΔT_m=0.1 (p.u.); CPSS (Dotted), PSOPSS (Dashed) and PSO-TVACPSS (Solid)
(a) P=0.8, Q=-0.2, X_e=0.3 (b) P=1.0, Q=-0.2, X_e=0.3 (c) P=0.8, Q=-0.2, X_e=0.6 (d) P=1.0, Q=-0.2, X_e=0.6

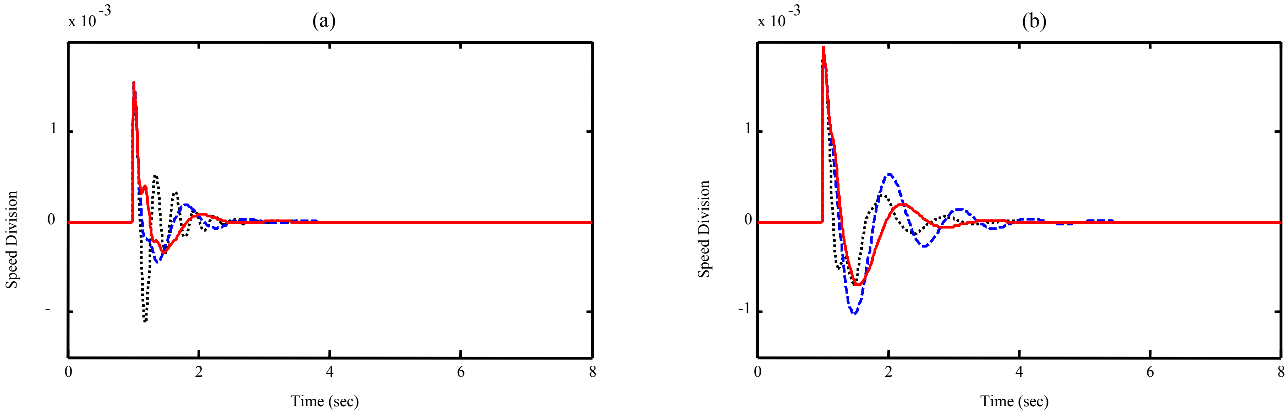

Figure 8. 3-φ to ground fault 100 ms for X_e=0.3, CPSS (Dotted), PSOPSS (Dashed) and PSO-TVACPSS (Solid)
(a) P=0.8, Q=0.4 (b) P=1.0, Q=0.5

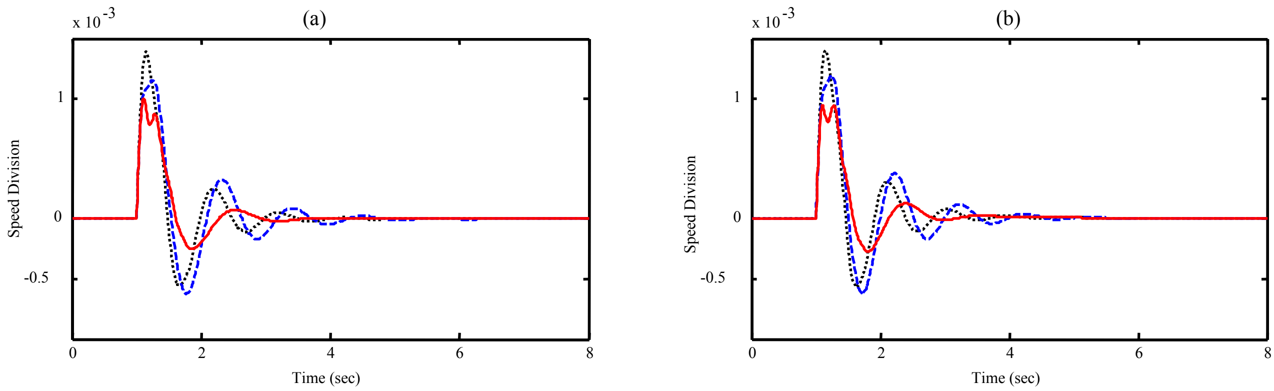

Figure 9. ΔT_m=0.1 (p.u.) under X_e=0.6 and H'=H/4, CPSS (Dotted), PSOPSS (Dashed) and PSO-TVACPSS (Solid)
(a) P=1.0, Q=0.5 (b) P=0.6, Q=0.0

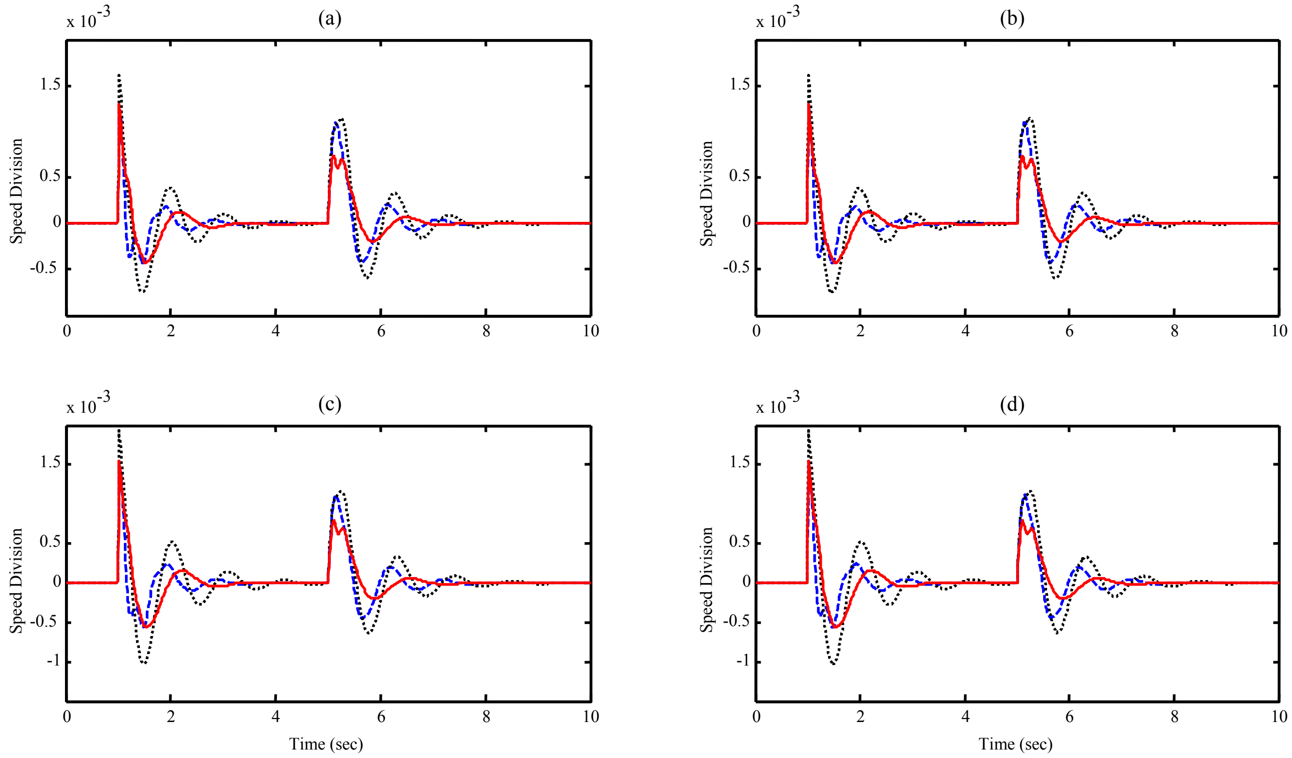

Figure 10. System response in scenario 3; CPSS (Dotted), PSOPSS (Dashed) and PSO-TVACPSS (Solid)
(a) P=0.8, Q=-0.2, X_e=0.3 (b) P=0.8, Q=0.0, X_e=0.6 (c) P=1.0, Q=-0.2, X_e=0.3 (d) P=1.0, Q=0.2, X_e=0.6 and H'=H/4

To demonstrate performance robustness of the proposed method, two performance indices: the Integral of the Time multiplied Absolute value of the Error (*ITAE*) and Figure of Demerit (*FD*) based on the system performance characteristics are defined as [16]:

$$ITAE = 1000 \int_0^{t_{sim}} t.\omega.dt \tag{11}$$

$$FD = (1000 \times OS)^2 + (2000 \times US)^2 + T_s^2 \tag{12}$$

$$IAE = 1000 \int_0^{t_{sim}} \omega.dt \tag{13}$$

$$ISE = 1000 \int_0^{t_{sim}} \omega^2.dt \tag{14}$$

where, Overshoot (*OS*), Undershoot (*US*) and settling time of rotor angle deviation of machine is considered for evaluation of the *FD*. It is worth mentioning that the lower values of these indices are, the better the system response in terms of time domain characteristics. Numerical results of performance robustness for all operating conditions as given in Table 1 for scenario 1 and 2 are listed in Tables 4-5.

It can be seen that the values of these system performance characteristics with the proposed PSO-TVAC based tuned PSS are much smaller compared to that PSO and classical based designed PSS. This demonstrates that the overshoot, undershoot, settling time and speed deviations of machine is greatly reduced by applying the proposed stabilizer.

VI. CONCLUSIONS

A PSO-TVAC optimization technique has been successfully applied for power system stabilizer design in a SMIB power system in this paper. To design PSS problem, a nonlinear simulation-based objective function is developed to improve the system damping and then PSO-TVAC algorithm is implemented to search for the optimal stabilizer parameters.

To improve optimization synthesis in the PSO, the concept of time-varying acceleration coefficients is used in addition to the time-varying inertia weight factor. It is easy to implement without additional computational complexity and has fewer control parameters to randomly adjustment than the PSO. Thereby, the ability to jump out the local optima, the convergence precision and speed are remarkably improved and thus the high precision and efficiency are achieved.

The effectiveness of the proposed PSO-TVAC based tuned stabilizer is demonstrated on a weakly connected example power system subjected to severe disturbance in comparison with PSO and classical methods based designed PSS to show its superiority. The nonlinear simulation results under wide range of operating conditions show the capability the proposed stabilizer to provide solution quality and efficient damping of low frequency oscillations and its superiority to the other methods.

Table 4. Performance indices value using different stabilizers in scenario 1

No	PSO-TVAC					PSO					CPSS				
	ITAE	*FD*	T_s	*IAE*	*ISE*×10^-4	*ITAE*	*FD*	T_s	*IAE*	*ISE*×10^-4	*ITAE*	*FD*	T_s	*IAE*	*ISE*×10^-4
1	0.878	5.321	1.590	0.012	3.095	1.251	6.464	1.620	0.015	3.910	1.663	7.279	1.710	0.017	4.544
2	0.522	2.783	1.100	0.016	1.215	0.762	3.174	1.100	0.023	1.465	0.861	3.931	1.102	0.028	1.803
3	1.186	7.494	1.730	0.002	5.340	1.794	10.09	2.090	0.009	7.226	1.919	12.35	2.560	0.019	9.093
4	0.878	5.321	1.590	0.012	3.095	1.251	6.464	1.620	0.015	3.910	1.663	7.279	1.710	0.015	4.444
5	0.522	2.783	1.100	0.016	1.215	0.762	3.174	1.100	0.023	1.465	0.461	2.931	1.100	0.028	1.603
6	1.186	7.494	1.730	0.002	5.340	1.794	10.09	2.090	0.009	7.226	1.919	11.32	2.560	0.019	9.093
7	0.879	5.343	1.600	0.011	3.106	1.254	6.481	1.620	0.015	3.925	1.663	7.284	1.710	0.015	3.448
8	1.184	7.473	1.730	0.002	5.320	1.790	10.05	2.080	0.009	7.196	1.919	12.37	1.560	0.009	4.088
9	0.521	2.776	1.100	0.016	1.210	0.760	3.167	1.100	0.023	1.460	1.461	4.931	1.100	0.022	1.503
10	1.187	7.500	1.730	0.002	5.350	1.790	10.05	2.080	0.009	7.196	1.918	12.35	1.960	0.009	4.086

Table 5. Performance indices value using different stabilizers in scenario 2

No	PSO-TVAC					PSO					CPSS				
	ITAE	*FD*	T_s	*IAE*	*ISE*×10^-4	*ITAE*	*FD*	T_s	*IAE*	*ISE*×10^-4	*ITAE*	*FD*	T_s	*IAE*	*ISE*×10^-4
1	0.767	2.501	1.420	0.302	2.707	1.118	4.738	1.700	0.309	4.868	1.476	4.573	1.850	0.308	5.085
2	1.137	2.738	1.420	0.402	3.226	1.495	5.247	1.730	0.403	5.616	1.810	5.099	1.830	0.403	5.901
3	0.820	2.625	1.420	0.268	2.879	1.178	4.915	1.760	0.279	5.218	1.597	4.783	1.890	0.279	5.481
4	0.767	2.501	1.420	0.302	2.707	1.118	4.738	1.700	0.309	4.868	1.476	4.573	1.850	0.308	5.085
5	1.137	2.738	1.420	0.402	3.226	1.495	5.247	1.730	0.403	5.616	1.810	5.099	1.830	0.403	5.901
6	0.820	2.625	0.420	0.268	2.879	1.178	4.915	1.760	0.279	5.218	1.597	4.783	1.890	0.279	5.481
7	0.767	2.501	1.420	0.301	2.707	1.118	4.738	1.700	0.309	4.868	1.477	4.574	1.850	0.308	5.086
8	0.820	2.626	1.420	0.268	2.879	1.179	4.916	1.760	0.279	5.219	1.597	4.784	1.890	0.279	5.483
9	1.137	2.738	1.420	0.402	3.226	1.495	5.247	1.730	0.403	5.616	1.810	5.099	1.830	0.403	5.901
10	0.820	2.625	1.420	0.268	2.879	1.179	4.916	1.760	0.279	5.218	1.597	4.784	1.890	0.279	5.482

APPENDIX

System Data

Generator: R_a=0, x_d= 2.0, x_q = 1.91, x'_d=0.244, x'_q=0.244, f = 50 Hz, T'_{do}=4.18, T'_{qo}=0.75, H=3.25

Transmission line: R=0, x_e=0.3

Exciter: K_A=50, T_A=0.05, E_{fdmax}=7.0, E_{fdmin}=-7.0

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