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# Improved Particle Swarm Optimization with Disturbance Term for Multi-machine Power System Stabilizer Design

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**Abstract:** Power system stabilizers (PSSs) are the most well-known and effective tools to damp power system oscillation caused by disturbances. To gain a good transient response, the design methodology of the PSS is quite important. The tuning of the PSS parameters for a multi-machine power system is usually formulated as an objective function with constraints consisting of the damping factor and damping ratio. The present paper, discusses a novel hybrid optimization technique to solve this kind of problem. A modified velocity updating formula of the particle swarm optimization (PSO) algorithm is declared. The addition of the disturbance term based on existing structure effectively mends the defects. The convergence of the improved algorithm is analyzed. Maximizations of the damping factor and the damping ratio of power system modes are taken as the goals or two objective functions, when designing the PSS parameters. The New England 16-unit 68-bus standard power system, under various system configurations and operation conditions, is employed to illustrate the performance of the proposed method. Eigenvalue analysis and nonlinear time domain simulation results demonstrate the effectiveness of the proposed algorithm. The results are very encouraging and suggest that the proposed PSO with the disturbance term (PSO-DT) algorithm is very efficient in damping low frequency oscillations and improving the stability of the power system. Simulation results demonstrated that the improved algorithm has a better performance than the standard one.

**Key words:** Particle Swarm Optimization, PSS Design, Multi-objective optimization, Disturbance Term

## INTRODUCTION

The dynamic stability of power systems is an important issue for secure system operation. Constantly increasing intricacy of electric power systems has enhanced interests in developing superior methodologies for power system stabilizers (PSSs). Transient and dynamic stability considerations are among the main issues in the reliable and efficient operation of power systems. Low frequency oscillation (LFO) modes have been observed when power systems are interconnected by weak tie-lines (Liu *et al*., 2004; Messina *et al*., 1998). The Low frequency oscillation mode, with weak damping, is also called the electromechanical oscillation mode and it usually happens in the frequency range of 0.1–2 Hz. PSSs are the most efficient devices for damping both local mode and inter-area mode small signal LFOs by increasing the system damping, thus enhancing the dynamic stability of the power systems (Anderson and Fouad, 1997). The generators are equipped with PSS which provides supplementary feedback and stabilizes the signal in the excitation system (Demello and Concordia, 1969; Rogers, 2000).

The problem of PSS design is to tune the parameters of the stabilizer so that the damping of the system's electromechanical oscillation modes is increased. This must be done without adverse effects on other oscillatory modes, such as those associated with the exciters or the shaft torsional oscillations. The stabilizer must also be so designed that it has no adverse effects on a system's recovery from a severe fault. The concept and parameters of PSS have been considered in various studies (Kundur, 1999; Kundur *et al*., 1989). Currently, many generating plants prefer to use conventional lead-lag structure of PSS (CPSS), due to the ease of online tuning and reliability (Hongesombut *et al*., 2004) and this may be pursuant to some problems behind utilizing the new methods.

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Intelligent optimization based methods have been initiated to solve the problems of PSS design (Abido, 1999; 2000; 2002; Abido and Abdel-Magid, 2002; 2003; Dubey and Gupta, 2005; El-Zonkoly *et al*., 2009). In this regard, two main techniques namely, sequential tuning and simultaneous tuning are used for the parameter tuning of PSS in power systems. To achieve a set of optimal PSS parameters under different operating conditions, the tuning and testing of PSS parameters must be repeated under different operating conditions of the system. The simultaneous tuning of PSS parameters is generally formulated as a very large scale non-linear and non-differentiable optimization problem. This type of optimization problem is very difficult to solve by applying traditional differentiable optimization algorithms. Many random investigating techniques, for instance, Tabu search (TS) (Abido, 1999) and simulated annealing (SA) (Abido, 2000), evolutionary programming (EP) (Abido and Abdel-Magid, 2002), genetic algorithm (GA) (Abido and Abdel-Magid, 2003; Dubey and Gupta, 2005), particle swarm optimization (PSO) (Abido, 2002; El-Zonkoly *et al*., 2009; Eslami *et al*., 2010), have recently gained acceptance due to their effectiveness and the ability to investigate the near-global optimal results in problem space. Deterministic techniques are relatively fast, but they might get trapped in the local optima since such problems might have many local solutions. A good initial point, or initial range, nevertheless, could lead to the global solution. On the other hand, stochastic methods are more appropriate for solving such type of problems because a wide range of values for parameters would be searched and probability of getting trapped into local optima would be reduced. However, their convergence in final steps of problem solving is very slow.

The GA is a stochastic, powerful and efficient optimization method, which has been recently utilized in determining PSSs parameters. While GA is satisfactory in finding near-global optimal result of the problem, it often yields revisiting the same sub-optimal solution and needs a very long run time that may be several minutes or even several hours depending on the size of the system under study. Particle Swarm Optimization (PSO) has some attractive characteristics compared to GA and other similar evolutionary techniques. PSO is a type of random search algorithm that simulates nature evolutionary process and shows excellent characteristic in solving some complex optimization problems. First, PSO requires very few parameters to adjust and thus it is convenient to parameter optimization where large amount of calculation are required. Secondly, PSO can discover the optimal solutions with a quick convergent speed, because it just has two computation formulas for iteration (Kennedy and Eberhart, 1995; Shi and Eberhart, 1998). In recent times, many researche works have been undertaken to modify the act of the standard PSO (SPSO) to improve its performance (He and Han, 2007).

One of the best improvements on the SPSO has been done by He and Han (2007). On account of the reason mentioned above, this paper presents a improved particle swarm optimization algorithm (PSO-DT) which add a disturbance term to the velocity updating equation based on the prototype of the standard PSO trying to improve (or avoid) the shortcoming of standard PSO. Of course, the PSO-DT doesn't exclude the improvement methods introduced above if they are indeed effective. It must be pointed out that before our work several papers have used disturbance to improve the performance of Standard PSO. Compared to SPSO, the method proposed by this paper realizes more easily and almost have the same effect to SPSO. Hence in this study, PSO-DT is used to determine the optimal gain and time constants of PSSs for the multi-machine system. The effectiveness of the proposed algorithm is investigated on a The New England 16-unit 68-bus standard power system under various operating conditions by eigenvalue analysis and some performance indices using a multi-objective function. It is shown that the PSO-DT method is able to provide efficient damping of low frequency oscillations. This provides an excellent negotiation opportunity for the system manager, manufacturer of the PSS and customers to pick out the desired PSS from a set of optimally designed PSSs. This paper is organized as follows. In Section 2, brief overviews of SPSO and PSO-DT optimization techniques are presented. The proposed controller structure and problem formulation are described in Section 3. The power system under study and simulation results are provided and discussed in Sections 4. Finally, conclusions are given in Section 5.

### *Optimization Overview:*

Optimization techniques are used to find a set of design parameters, $X = \{x_1, x_2,..., x_n\}$, of a system, that can lead the system to its optimal conditions. In a more advanced formulation the objective function, $f(X)$, to be minimized or maximized, might be subject to constraints in the form of equality constraints, inequality constraints and/or parameter bounds.

A general constrained nonlinear optimization problem can be defined as follows:

$$\begin{aligned} &Minimize \quad f(X) \\ &Subject\ to \quad g_i(X) \le 0 \qquad i = 1,2,\ldots,p \\ &\qquad\qquad\quad h_i(X) = 0 \qquad j = 1,2,\ldots,m \\ &\qquad\qquad\quad L_k \le X_k \le U_k \quad k = 1,2,\ldots,n \end{aligned} \tag{1}$$

where $X$ is $n$ dimensional vector of design variables, $f(X)$ is the objective function. $g(X)$ and $h(X)$ are inequality and equality constraints respectively. $L_k$ , $U_k$ are lower and upper band constraints. In the presented work, the parameters of PSS are determined by optimization. The objective function in this case is defined as Eq. (10). The optimization technique is used to determine the decision variables, i.e., the PSSs parameters, so that the objective function given in Eq. (10) would be minimized.

***Particle Swarm Optimization:***

Particle swarm optimization is a population based stochastic optimization method. It explores for the optimal solution from a population of moving particles, based on a fitness function. Each particle represents a potential answer and has a position $(X_i^k)$ and a velocity $(V_i^k)$ in the problem space. Each particle keeps a record of its individual best position $(P_i^k)$, which is associated with the best fitness it has achieved thus far, at any step in the solution. This value is known as *pbest.* Moreover, the optimum position between all the particles obtained so far in the swarm is stored as global best position $(P_g^k)$. This location is called *gbest.* The velocity of particle and its new position will be updated according to the following equations and Fig. 1(Kennedy and Eberhart, 1995):

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{2}$$

$$V_i^{k+1} = w \times V_i^k + c_1 \times r_1 \times (P_i^k - X_i^k) + c_2 \times r_2 \times (P_g^k - X_i^k) \tag{3}$$

where $w$ is an inertia weight that controls a particle's exploration during a search, $c_1$ and $c_2$ are positive numbers explaining the weight of the acceleration terms that guide each particle toward the individual best and the swarm best positions respectively, $r_1$ and $r_2$ are uniformly distributed random numbers in (0, 1), and $N$ is the number of particles in the swarm. The inertia weighting function in Eq. (3) is usually calculated using following equation:

$$w = w_{max} - (w_{max} - w_{min}) \times x\ k / G \tag{4}$$

where $w_{max}$ and $w_{min}$ are maximum and minimum value of $w$, $G$ is the maximum number of iteration and $k$ is the current iteration number. The first term in Eq. (3) enables each particle to perform a global search by exploring a new search space. The last two terms in Eq. (3) enable each particle to perform a local search around its individual best position and the swarm best position.

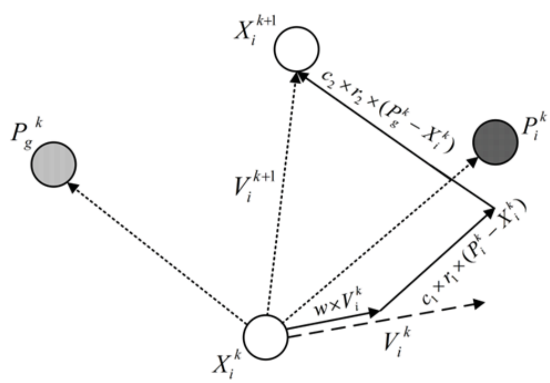


**Fig. 1:** Position update of particle in PSO

***B The Improved PSO with Disturbance Term (PSO-DT):***

In this paper, a modified particle swarm optimization with the disturbance term (PSO-DT) is proposed to optimally tune PSS in multi-machine power systems. (PSO-DT) which add a disturbance term to the velocity updating equation based on the prototype of the standard PSO trying to improve (or avoid) the shortcoming of standard PSO. The theory of PSO-DT (He and Han, 2007) creates an additional part at the end of the velocity update in Eq. (3) of SPSO known as disturbance term part. From the definitions above, the third part of Eq. (3): $\alpha \times (r_3 - 0.5)$ can be defined as disturbance term. However, adding the disturbance term model to the SPSO may increase its performance. The update velocity equation in hybrid PSO with the disturbance term (PSO-DT) is defined as:

$$V_i^{k+1} = w \times V_i^k + c_1 \times r_1 \times (P_i^k - X_i^k) + c_2 \times r_2 \times (P_g^k - X_i^k) + \alpha \times (r_3 - 0.5) \quad (5)$$

Position updating equation:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (6)$$

Where $\alpha$ is a small constant, $r_3$ is a number randomly distribution in the (0, 1) range, the others parameters is the same as standard PSO. In the early calculation, because $\alpha$ is very small compared to anterior three terms, and the mean value of $(r_3 - 0.5)$ equal to zero, the disturbance term even can be ignored since it exert little impact on the updating and searching capability of the whole optimization. While in the middle and later phases, when the velocity becomes slower and slower, the disturbance term ensures the searching velocity of particles will not drop down to zero, and as a result, the optimization will not stagnate, thus enabling the update to continue and overcoming the defects of easily falling into local optima of the standard PSO, therefore getting a more exact solution. The detailed procedure for updating the position and velocity of individuals for PSO-DT algorithm is presented in Fig.2.

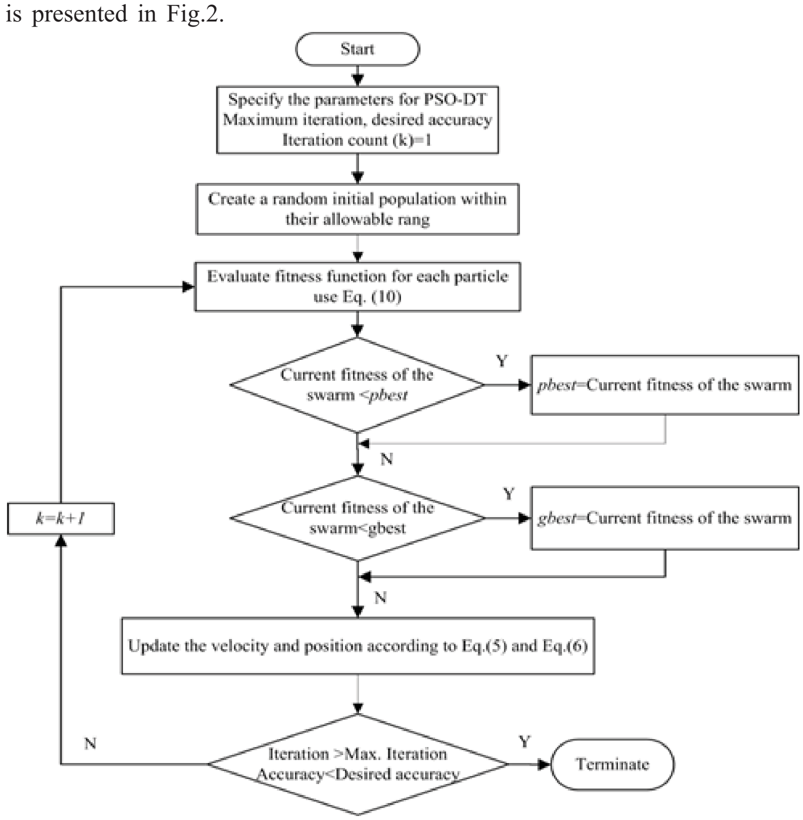


**Fig. 2:** Flowchart of the PSO-DT used for the optimization of PSS parameters

***Optimal tuning of PSSs parameters:***

***Power System Model:***

In this study, each generator is modeled as a two-axis, six-order model. For all operating conditions, the power system with generators, PSSs, and excitation systems can be modeled by a set of nonlinear differential equations as:

$$\square = f(x,\ u) \tag{7}$$

where x = [$\Delta\delta$, $\Delta\omega$, $E_q'$, $\psi_d''$, $E_d'$, $\psi_q''$] and u are the vector of state variables and the vector of the PSS output signals, respectively. The vector of state variables include the speed deviation ($\Delta\omega$), rotor angle ($\Delta\delta$), the d- and q-axis component of stator voltage ($E_q$, $E_d$), and the d- and q-axis component of stator flux ($\psi_d$ , $\psi_q$) respectively. In the PSS design, the power system is usually linearized in terms of a perturbed value in order to perform the small signal analysis. Therefore the system in Eq. (7) is linearized around an equilibrium operating point of the power system. Eq. (8) describes the linear model of the power system:

$$\begin{aligned} \square &= Ax + Bu \\ y &= Cx + Du \end{aligned} \tag{8}$$

where $A$ is the power system state matrix, $B$ is the input matrix, $C$ is the output matrix, $D$ is the feed-forward matrix. From Eq. (8), the eigenvalues $\lambda_i = \sigma_i \pm \omega_i$ of the total system can be evaluated.

The PSSs with a lead-lag structure of speed deviation input are considered in this study, and the transfer function of the PSS is given by Eq. (9). The structure of PSS is shown in Fig.3. It consists of a gain block with gain $K_i$, a signal washout block and two-stage phase compensation blocks.

$$U_i = K_i\left(\frac{sT_w}{1+sT_w}\right)\left[\frac{(1+sT_{1i})(1+sT_{3i})}{(1+sT_{2i})(1+sT_{4i})}\right]\Delta\omega_i(s) \tag{9}$$

where $\Delta\omega_i$ and $U_i$ are the perturbations of the synchronous speed and the output voltage signal respectively, which are added to the excitation system reference perturbation. The signal washout block acts as a high-pass filter, with the time constant $T_w$ that allows the signal associated with the oscillations in rotor speed to pass unchanged, and it does not allow the steady state changes to modify the terminal voltages. From the view of the washout function, the value of $T_w$ is generally not critical and may be in the range of 0.5 to 20 seconds. In this study, it is fixed as 10s. The phase compensation blocks with time constants $T_1$, $T_2$ and $T_3$, $T_4$ supply the suitable phase-lead characteristics to compensate for the phase lag between the input and the output signals. The five PSS parameters consisting of the four time constants $T_1$ to $T_4$ and the gain $K$ need be optimally chosen for each generator to guarantee optimal system performance under various system configurations and disturbances.

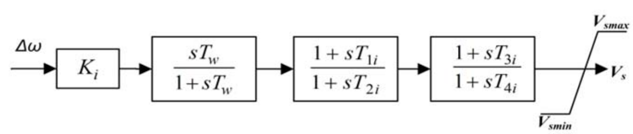


**Fig. 3:** Structure of power system stabilizer

***B Objective function:***

During an unstable condition, the declining rate of the power system oscillation is determined by the highest real part of the eigenvalue (damping factor) in the power system and the magnitude of each oscillation mode is determined by its damping ratio. Hence, the objective functions naturally contain the damping ratio and the damping factor in the formulation for the optimal setting of PSS parameters. The problem of the robust PSS design is formulated as a multi-objective optimization problem to solve it. Therefore, for the optimal tuning of PSS parameters, a multi-objective function may be formulated as follows:

$$Minimize\ f = \sum_{\substack{i=1 \\ \sigma_i \geq \sigma_0}}^{n} (\sigma_0 - \sigma_i)^2 + \varpi . \sum_{\substack{i=1 \\ \xi_i \geq \xi_0}}^{n} (\xi_0 - \xi_i) \tag{10}$$

*Subject to*

$$\begin{cases} k_{i\,min} \le k_i \le K_{i\,max} \\ T_{1i,min} \le T_{1i} \le T_{1i,max} \\ T_{2i,min} \le T_{2i} \le T_{2i,max} \qquad i=1,\ 2,\ldots,16 \\ T_{3i,min} \le T_{3i} \le T_{3i,max} \\ T_{4i,min} \le T_{4i} \le T_{4i,max} \end{cases} \tag{11}$$

where $i=1,2,\ldots,n$. $n$ is the number of eigenvalue and $\sigma_i$ is the real part of the $i$th eigenvalue (damping factor) and $\xi_i = -\sigma_i / \sigma i_i{}^2+\omega_i{}^2$ is the damping ratio of the $i$th eigenvalue. $\sigma_0$ is a constant value of the expected damping factor. The worthwhile level of the system damping is represented by the value of $\sigma_0$. This level can be obtained by shifting the dominant eigenvalues to the left of $s=\sigma_0$ line in the $s$-plane. $\xi_0$ is a constant value of the expected damping ratio and the desired minimum damping ratio. $v$ is a weight for combining both damping factors and damping ratios. The constraint set is made up of bounds of PSS parameters, which can be formulated as Eq. (11).

The objective function only forces the unstable or poorly damped electromechanical oscillation modes to be relocated to the left side of the s-plane. Fig. 4 shows this method's performance. In the Eq. (10), the damping ratio difference is less than 1. if we take square for this term for each unit, then the objective function is unable to determine the optimum solution. The best objective value is zero for this function. The proposed approach employs PSO-DT to solve this optimization problem and search for an optimal set of PSS parameters, $K_i$ , $T_{1i}$ , $T_{2i}$ , $T_{3i}$ and $T_{4i}$ ; $i=1,2,3,4,\ldots,16$.

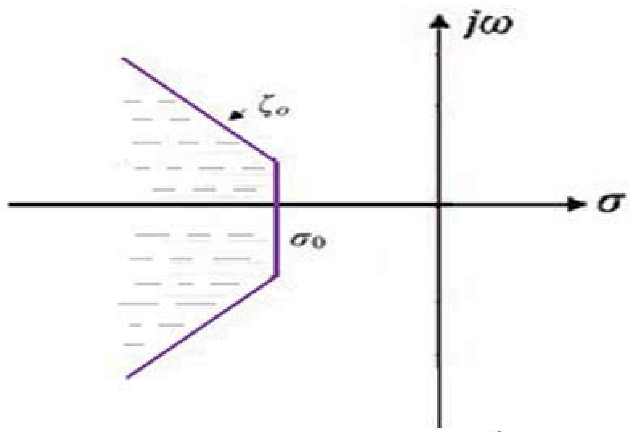


**Fig. 4:** Region of eigenvalue location for objective function f

***Simulation Results:***

The New England 16-machine, 68-bus system is used to illustrate the performance of the proposed method. The system data of the 68-bus New England test system (NETS)–New York (NYPS) interconnected system is given in (Rogers, 2000). Fig. 5 presents the one-line diagram of the system. There are 68 buses and 16 generators in this system. Generators $G_1$–$G_9$ are in New England, generators $G_{10}$–$G_{13}$ are in New York and $G_{14}$–$G_{16}$ are equivalent generators in the neighborhood of New York. The entire system can be divided into five areas, (i) New England ($G_1$-$G_9$), (ii) New York ($G_{10}$-$G_{14}$), (iii) Generator $G_{14}$, (iv) Generator $G_{15}$ and (v) Generator $G_{16}$. This system, which is unstable without PSS, has been widely used as a benchmark system for PSS parameter tuning problems. There are 11 modes that are unstable or have damping ratios less than 0.05. All these are electromechanical modes. This represents the total complement of electromechanical oscillatory modes in this 16 generator system. In the test system, all generators are equipped with PSSs, and generator parameters are modified to add sub-transient parameters.

There are four operating conditions considered in this work and it is as follows:

- Case 1: Base case.
- Case 2: Tie lines 1-2 out-of-services.
- Case 3: Tie lines 25-26 and 3-18 are out-of-service.

In the tuning process, the constraints on PSS time constants $T_{1i}$ to $T_{4i}$ are set with the lower limit at 0. 01 s and the upper limit at 2.0 s, and the gain $K_i$ of PSS ranges from 1 to 50. There are 80 real variables and 16 integer variables to be optimized in this system. Parameters $\sigma_0$ and $\xi_0$ are set to be -1.0 and 15%, respectively. The target values of the maximum damping factor and the minimum damping ratio are assumed to be the desired limit value of all eigenvalues in the study system. The weight parameter $v$ is set to be 1.35, which is derived from the experiences of many experiments conducted on this problem. In order to receive optimum performance, number of particle, particle size, number of iteration, $c_1$, $c_2$, $\alpha$ and $c$ is selected as 20, 9, 100, 2, 2, 0.04 and 1, respectively. Also, the inertia weight, $w$, is linearly decreasing from 0.9 to 0.4. It should be noted that PSO-DT algorithm is needed to be applied multiple of times for optimum tuning of PSS parameters selection. The final values of the optimized parameters with the objective function $f$ by PSO-DT method are presented in Table I. It shows the values of the parameters corresponding to the best fitness achieved by the algorithm after 10 trials.

The principal eigenvalues, oscillation frequencies, and damping ratios obtained for all operating conditions without PSS and after application of various optimization methods in the system are given in Table II. In Table II, the boldface value represents the biggest damping factor, and the value highlighted represents the smallest damping ratio. All damping factors are smaller than -1.0 and all damping ratios are greater than 0.15 when the proposed method is applied. From Fig. 6 it not only shows that the proposed PSO-DT can shift the unstable or lightly damped oscillation modes but also shift other oscillation modes more to the left in the s-plane.

A number of time domain simulations were performed to demonstrate the effectiveness of tuning parameters of PSSs using the proposed PSO-DT method. In these tests, a three phase fault was applied on bus 25 for 50 ms, after which the fault was cleared and the line between buses 25–26 was tripped. The oscillations in the speed deviations, electrical powers and field voltages of all the generators for the base case without PSS are given in Fig. 7-9. From Fig. 7-9, it is observed that the oscillations in the speed deviations, electrical powers and field voltages increase with time. These oscillations are due to the unstable and under damped modes present in the system. The oscillations in the speed deviations, electrical powers and field voltages obtained by the proposed method for all the generators are given in Fig. 10-12. It is observed from Fig. 10-12 that, with the proposed method, the oscillations are damped. These time domain simulations agree well with the results of eigenvalue analysis.

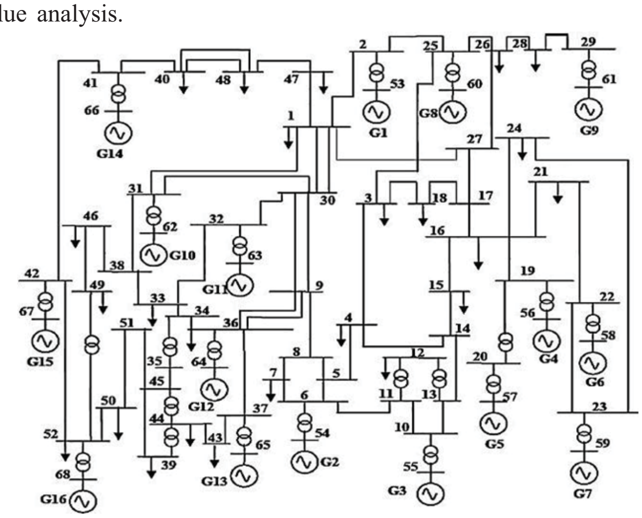


**Fig. 5:** Single line diagram 16 generator system

**Table 1:** searched gains and time constants of PSSs by the PSO-DT

| | unit | *K* | *T1* | *T2* | *T3* | *T4* |
|---|---|---|---|---|---|---|
| *PSO-DT optimized parameters* | G1 | 10.934 | 0.1 | 0.025 | 0.0800 | 0.02 |
| | G2 | 9.956 | 1.1294 | 0.0361 | 0.1021 | 0.0348 |
| | G3 | 14. 567 | 0.0675 | 0.0231 | 0.0631 | 0.0364 |
| | G4 | 15.976 | 0.0356 | 0.0251 | 0.0815 | 0.0384 |
| | G5 | 28.543 | 0.0489 | 0.0251 | 0.0825 | 0.6231 |
| | G6 | 12.644 | 0.1070 | 0.0491 | 0.1032 | 0.07001 |

**Table 1:** Continue

| | | | | | |
|---|---|---|---|---|---|
| G7 | 27.845 | 0.0653 | 0.0251 | 0.0800 | 0.2180 |
| G8 | 15.654 | 0.0512 | 0.0235 | 0.0599 | 0.3011 |
| G9 | 24.355 | 0.0834 | 0.0153 | 0.0500 | 0.267 |
| G10 | 15.848 | 0.5070 | 0.0440 | 0.0887 | 0.0650 |
| G11 | 21.309 | 0.0675 | 0.0160 | 0.0541 | 0.0258 |
| G12 | 13.355 | 0.0356 | 0.0100 | 0.0389 | 0.0200 |
| G13 | 10.755 | 0.0512 | 0.0241 | 0.0500 | 0.0767 |
| G14 | 10.455 | 0.1907 | 0.0161 | 0.1021 | 0.0348 |
| G15 | 26. 308 | 0.0675 | 0.0231 | 0.0731 | 0.0464 |
| G16 | 15.099 | 0.1256 | 0.0251 | 0.0715 | 0.0284 |

**Table 2:** Eigenvalues, oscillation frequencies, and damping ratios with and without PSSs

| | Case 1 | Case 2 | Case 3 |
|---|---|---|---|
| Without PSSs | 0.0352±7.2450i, 1.153, -0.004 | 0.0164±7.2158i,1.148,-0.002 | 0.2530±6.9023i,1.098,-0.036 |
| | 0.3863±7.3515i, 1.170, -0.052 | 0.3386±7.3162i,1.164,-0.046 | 0.0180±6.9629i,1.108,-0.002 |
| | 0.3021±7.6355i, 1.215, -0.039 | 0.2931±7.6279i,1.214,-0.038 | 0.2997±7.6362i,1.215,-0.039 |
| | -0.5049±7.7197i, 1.228, 0.065 | -0.5043±7.7115i,1.227,0.065 | -0.5062±7.7204i,1.228,0.065 |
| | 0.1291±8.3497i, 1.328, -0.015 | 0.1213±8.2746i,1.316,-0.014 | -0.3551±8.2276i,1.309,0.043 |
| | 0.3018-8.4069i, 1.338, -0.035 | 0.2923±8.4056i,1.337,-0.034 | 0.0002±8.339i,1.3272-0.00003 |
| | -0.5235±8.9555i, 1.425, 0.058 | -0.3718±8.7118i,1.386,0.042 | 0.2946±8.4113i,1.338,-0.035 |
| | -0.4275±9.6674i, 1.538, 0.044 | -0.4291±9.6662i,1.538,0.044 | -0.4477±9.6611i,1.537,0.046 |
| | -0.1687±9.9130i, 1.577, 0.017 | -0.1744±9.9157i,1.578,0.017 | -0.1775±9.9009i,1.575,0.017 |
| | -1.0550±10.998i, 1.750, 0.095 | -1.0436±11.0584i,1.76,0.093 | -1.0442±11.074i,1.762,0.093 |
| | 0.2463±12.109i, 1.927, -0.020 | 0.2375±12.033i,1.915,-0.019 | 0.2381±12.106i,1.926,-0.019 |
| *With PSO_DT* | -1.4279±6.6134i, 1.052, 0.211 | -1.4254±5.0306i,1.043,0.212 | -1.1619±6.3213i,1.006,0.180 |
| | -1.4121±6.8624i, 1.092, 0.201 | -1.4017±6.8511i, 1.090,0.200 | -1.37906±6.469i,1.029,0.208 |
| | -2.1773±6.9188i, 1.101, 0.300 | -2.1717±6.9147i,1.100,0.299 | -2.17463±6.924i,1.101,0.299 |
| | -1.5263±7.7041i, 1.226, 0.194 | -1.4387±7.5921i,1.208,0.186 | -1.546±7.65937i,1.219,0.197 |
| | -2.2668±7.5335i, 1.993, 0.288 | -2.2695±7.5470i,1.201,0.287 | -3.0042±7.2412i,1.152,0.383 |
| | -2.6031±8.2160i, 1.307, 0.302 | -3.61147±7.764i,1.235,0.421 | -2.2674±7.5520i,1.201,0.287 |
| | -4.4179±7.7750i, 1.237, 0.494 | -2.5808±8.2131i,1.307,0.299 | -2.5807±8.2131i,1.307,0.299 |
| | -4.3223±7.9556i, 1.266, 0.477 | -4.3734±7.9821i,1.270,0.480 | -4.3393±8.0081i,1.274,0.476 |
| | -4.7632±7.7182i, 1.228, 0.568 | -4.6165±7.7287i,1.230,0.566 | -4.3010±7.7375i,1.231,0.565 |
| | -2.7004±10.950i, 1.742, 0.239 | -2.6737±10.915i,1.737,0.237 | -2.7057±10.948i,1.742,0.239 |
| | -3.8766±13.050i, 2.076, 0.284 | -3.923±13.2357i,2.106,0.284 | -3.8872±13.243i,2.107,0.281 |

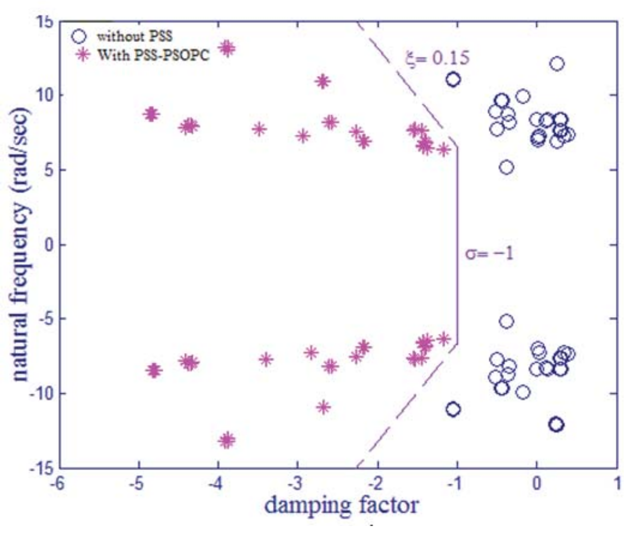


**Fig. 6:** The searched eigenvalues with the objective function F for the three cases.

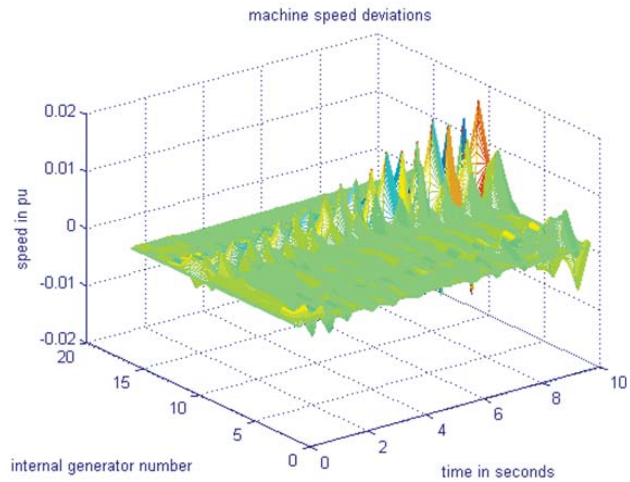


**Fig. 7:** Speed deviation of all the generators in 3D without PSS

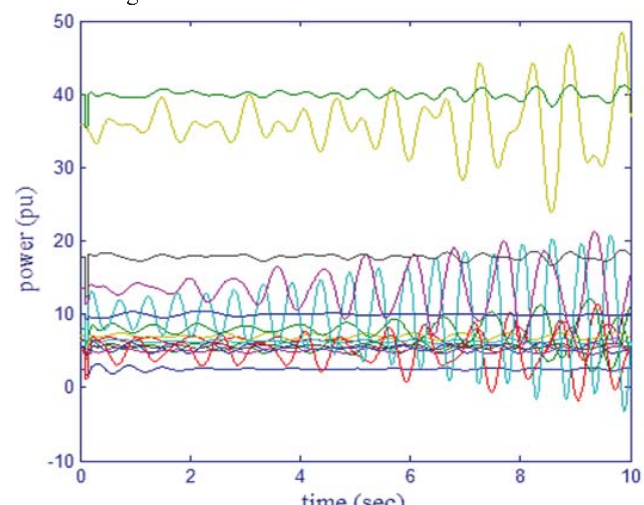


**Fig. 8:** Electrical power of all machines without PSS

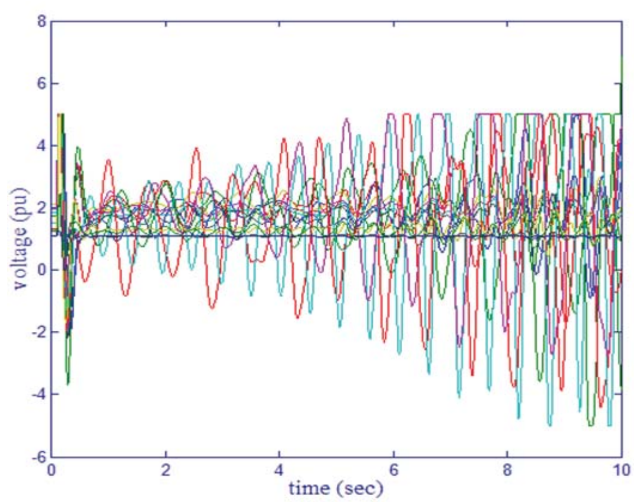


**Fig. 9:** Field voltages of all the generators without PSS

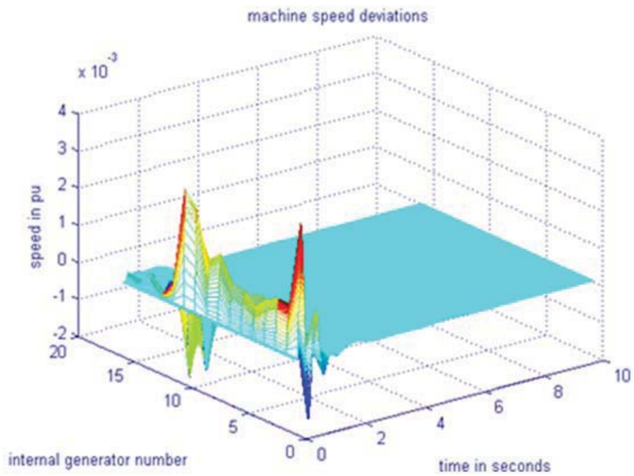


**Fig. 10:** Speed deviation of all the generators in 3D with the proposed method

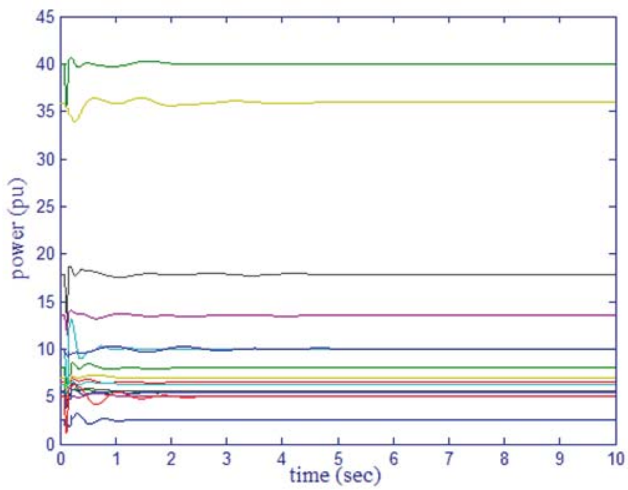


**Fig. 11:** Electrical powers of all machines with proposed method

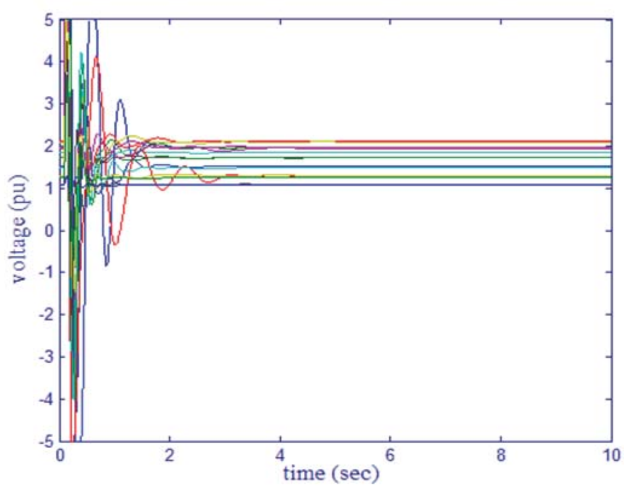


**Fig. 12:** Field voltages of all the generators with proposed method

***Conclusion:***

In the present paper, an application of a modified PSO with the disturbance term algorithm to determine the optimal tuning of PSSs parameters is introduced. The design problem of PSSs parameters selection is converted into an optimization problem which is solved by the PSO-DT technique with the eigenvalue-based multi-objective function. Maximization of the minimum damping ratio and minimum damping factor of dominant oscillatory modes are employed as two objectives to optimize the PSS parameters. Eigenvalue analysis shows acceptable damping of system modes, particularly the low-frequency modes, when the PSSs are tuned by PSO-DT. Time domain simulations also show that the oscillations of synchronous machines can be rapidly damped for power systems with the proposed PSSs over a wide range of conditions. Based on ten trial runs, it is observed that the PSO-DT consistently performs the best in solving the tuning problem. This indicates the efficiency of the proposed PSO-DT algorithm in tuning PSS and stabilizing the system under LFOs.

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