International Journal of Electrical and
Electronics Engineering (IJEEE)
ISSN(P): 2278-9944; ISSN(E): 2278-9952
Vol. 3, Issue 6, Nov 2014, 11-22
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International Academy of Science, Engineering and Technology
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A NOVEL PSO ALGORITHM FOR OPTIMAL POWER SYSTEM STABILIZER

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ABSTRACT

The affirmative outcome of PSS on Low Frequency Oscillations (LFO) damping is apparently clear. Appropriate designing of PSS can increase the affirmative outcome. As a result, to improve the effectiveness, this project submits a different scheme to reduce LFO. As the trouble of PSS design can be taken into account as a multi-objective optimization problem, this project proposes an improved Particle Swarm Optimization (IPSO) algorithm, which is a novel heuristic optimization algorithm, to improve the searching space and union speed of the Conventional PSO (CPSO) algorithm. A proper and inclusive fitness function is also introduced to obscure the extensive operating terms. In that way, this algorithm is working to recognize the optimal parameters of PSS for Single Machine related to Infinite Bus (SMIB) system by minimizing the fitness function. Simulation results indicate the superiority of the proposed algorithm.

KEYWORDS: Damping Torque, Stability, Swarm Intelligence, LFO, PSO, PSS, SMIB

INTRODUCTION

Particle swarm optimization is a heuristic global optimization method submit originally by Doctor Kennedy and Eberhart in 1995(Kennedy J, Eberhart R, 1995; Eberhart R, Kennedy J, 1995) It is developed from swarm intelligence and is derived from the research of bird and fish flock passage performance. While searching for food, the birds are either scattered or go together before they trace the place where they can find the food. While the birds are searching for food from one place to another, there is always a bird that can smell the food very well, that is, the bird is observable of the place where the food can be found, having the better food resource information. Because they are passing the information, especially the good information at any time while searching the food from one place to another, conducted by the good information, the birds will finally flock to the place where food can be found. To the extent that particle swam optimization algorithm is concerned, solution swam is compared to the bird swarm, the birds' moving from one place to another is equal to the development of the solution swarm, good information is equal to the most optimist solution, and the food resource is equal to the most optimist solution during the whole course. The most optimist solution can be worked out in particle swarm optimization algorithm by the assistance of every individual. The particle without quality and volume serves as every individual, and the simple behavioral pattern is synchronized for every particle to make clear the density of the whole particle swarm. This algorithm can be used to work out the complex optimist problems. Owing to its many merits including its simplicity and easy implementation, the algorithm can be used widely in the fields such as function optimization, the model classification, machine study, neutral network training, the signal procession, vague system control, automatic adaptation control and etc (Zheng Jianchao, Jie Jing, Cui Zhihua, 2004, (In Chinese)).

PSO ALGORITHM

- **CPSO Algorithm**

The CPSO algorithm is a relatively new generation of combinatorial metaheuristic algorithms, which is fitted for optimizing complex numerical. In the basic particle swarm optimization algorithm, particle swarm consists of "n" particles, and the location of every particle endures for the prospective clarification in D-dimensional space. The particles modify its circumstance according to the following three principles:

(1) to remain its inertia (2) to modify the condition according to its most optimist location (3) to modify the condition as per the swarm's most optimist location. The location of every particle in the swarm is affected both by the most optimist location during its movement (individual practice) and the location of the most optimist particle in its surrounding (near practice). When the whole particle swarm is adjoining the particle, the most optimist location of the adjoining is equal to the one of the whole most optimist particle; this algorithm is called the whole PSO. If the slight adjoining is used in the algorithm, this algorithm is called the partial PSO.

CPSO starts with the random initialization of a swarm of particles in the search space and works on the social behavior of the particles in the swarm. As a result, it finds the global best solution by simply adjusting the trajectory of every particle towards its own best location and towards the best particle of the swarm at every time step (generation). Though, the trajectory of every particle in the search space is adapted by dynamically altering the location and velocity of every particle, according to its own flying practice and the flying practice of the other particles in the search space. The location and velocity of every particle are updatedin every iteration according to the following equations:

$$v_i'^d = w\, v_i^d + c_1 r_1 (x^d_{pbesti} - x_i^d) + c_2 r_2 (x^d_{gbesti} - x_i^d) \quad (1)$$

$$x_i'^d = x_i^d + v_i'^d \quad (2)$$

where $x_i'^d$ and x_i^d represent the current and previous locations in the d th iteration of particle i, respectively; $v_i'^d$ and v_i^d are the current and previous velocities of particle i, respectively; x_{pbesti} and x_{gbest} are the best location found by particle i, so far and the best location found by the whole swarm so far, respectively; $\omega \in (0, 1)$is an inertia weight, which determines how much the previous velocity is preserved; c_1 and c_2 are positive constant parameters called acceleration coefficients; and r_1 and r_2 are two independent random number suniformly distributed in the range of [0, 1].

In CPSO, Equation (4) is utilized to update the new velocity according to its previous velocity and the distance of its current location from both its own personal best location and the global best location. The value of every velocity can be usually bounded to the range $[v_{\min}, v_{\max}]$ to control excessive roaming of the particles outside the search space $[x_{\min}, x_{\max}]$. Then the particle flies toward a new location according to Equation (2). The procedure is repeated until a stopping criterion is reveryed.

Based on defining the neighborhood for every particle, there are two major models of CPSO algorithm called the global best and local best. In the local best model, the neighborhood of a particle is defined by several fixed particles while in the global best model; the neighborhood of a particle consists of the particles in the whole swarm. Although, these models give different performances on different problems, but global best model has a faster convergence speed and a higher probability of getting stuck in local optima (Poli et al.). The procedure of CPSO is summarized as follows:

Step 1: Initialize a swarm of particles with random locations and velocities.

Step 2: Evaluate the fitness values of all particles, set *Pbest* of every particle and its fitness value equal to its current location and fitness value, and set *gbest* and its fitness value equal to the location and fitness value of the best initial particle.

Step 3: Update the velocity and location of every particle according to Equations (1) and (2), respectively.

Step 4: Evaluate the fitness values of all particles.

Step 5: For every particle, compare its current fitness value with the fitness value of its *pbest*. If current value is better, then update *pbest* and its fitness value with the current location and fitness value.

Step 6: Determine the best particle of current whole swarm with the best fitness value. If the fitness value is better than the fitness value of *gbest*, then update *gbest* and its fitness value with the location and fitness value of the current best particle.

Step 7: If a stopping criterion is met, then output *gbest* and its fitness value; otherwise go to Step 3.

- **The Proposed PSO Algorithm**

Although CPSO has shown some important advances by providing high speed of convergence in specific problems; however it does exhibits some shortages. It sometimes is easy to be trapped in local optimum, and the convergence rate decreased considerably in the later period of evolution; when reverying a near optimal solution, the algorithm stops optimizing, and thus the achieved accuracy of algorithm is limited. Several modifications have been proposed in literature to improve the performance of CPSO. Most of them are from one of the four categories: swarm topology, diversity maintenance, combination with auxiliary operations, and adaptive PSO.

Adaptation is the most promising category in PSO. Many approaches are attempted to improve the performance of CPSO by adaption of inertia weight. Empirical studies of PSO with inertia weight have shown that a relatively large inertia weight have more global search ability while a relatively small inertia weight results in a faster convergence. Consequently, the inertia weight decreases as a linear or nonlinear function of iterative generation. In addition to efficiently control the local search and convergence to the global optimum solution, time-varying acceleration coefficients were proposed in addition to the time-varying inertia weight factor. Since the search process of PSO is nonlinear and highly complicated, linearly and nonlinearly decreasing inertia weight and acceleration coefficients with no feedback taken from the global optimum fitness cannot truly reflect the actual search process. In fact, if the global fitness is large, the particles are far away from the optimum point. Hence, a big velocity is needed to globally search the solution space and so the inertia weight and acceleration coefficients must be larger values.

Motivated by the aforementioned, in this project, the inertia weight and acceleration coefficients are set as a function of global optimum fitness during search process of PSO algorithm. Based on this, two modifications are incorporated into the CPSO algorithm that prevents local convergence and provides excellent quality of final result. In this case, these parameters dynamically modify according to the rate of global fitness improvement as follows:

$$c_i = 1+1/\,[1+\exp(-\beta\times F(G_j))^{\alpha}], i=1, 2 \quad (3)$$

$$\omega=1/\,[1+\exp(-\beta\times F(G_j))^{\alpha}] \quad (4)$$

Initialize the swarm in an$M$-dimensional space//$M$is the number of system parameters

DO

// fitness evaluation and updating global memories

Evaluate fitness of particles, then

FOR i = 1 to number of particles

IF $f(X_i) < f(Pi)$**THEN** $P_i = X_i, f(Pi) = f(Xi)$

IF $f(Xi) < f(G)$ **THEN** $G = Xi$ **,** $f(G) = f(Xi)$ $P_i = X_i, (P_i) = f(X_i)$

END FOR

// inertia weight and acceleration coefficients calculation

Calculate ω **using Equation (3)**

Calculate $c_1$andc_2 **using Equation (4)**

// updating velocity and locations of particles

Calculate new velocity of the particles using Equation (1)

Calculate new location of the particles using Equation (2)

UNTIL stop criteria is satisfied.

Figure 1: The Pseudo-Code of Proposed PSO

Where F (G_t) is the fitness of global optimum in t-th iteration. The parameters α and β need to be predefined. The value of β can be set to the inverse of the value of global optimum fitness in the first iteration, i.e. $\beta = 1/F(G_1)$). Through the study of the non linear modulation parameter α and β reasonable set of choice for this parameter is derived within the range (1, 2). Moreover, under the assumption and definition above, it can be concluded that $0.5 \leq \omega < 1$, $1.5 \leq c_1 < 2$ and $1.5 \leq c_2 < 2$. Considering Equations (3) and (4), it isobvious that the bigger global fitness requires the bigger inertia weight and the bigger accelerate coefficients, and vice versa. Therefore, until the fitness of global optimum does not improve significantly, the inertia weight and accelerate coefficients are big since it still needs globally explore the search space to give the algorithm a better ability to rapidly search and move out of the local optima. Conversely, these parameters decrease fast to facilitate finer local explorations since global optimum solution reveryes a near optimum. The most important advantages of the proposed algorithm are to achieve faster convergence speed and better solution accuracy with minimum incremental computational burden. Figure 1 illustrates the pseudo-code of proposed PSO.

PROBLEM FORMULATION

The stability maintenance in a power system is considered as one of the most significant and essential aspect of power systems quality. In this section, the design procedure is described. Figure 2 shows the system under study, which represents a Single Machine Infinite Bus system (SMIB). The nonlinear equations of the system are given as Equation (5).

Equations

The above equations can be linearized for small oscillation around an operating point [1, 2, 5, and 6] and can be illustrated in the block diagram as shown in Figure 2 as well.

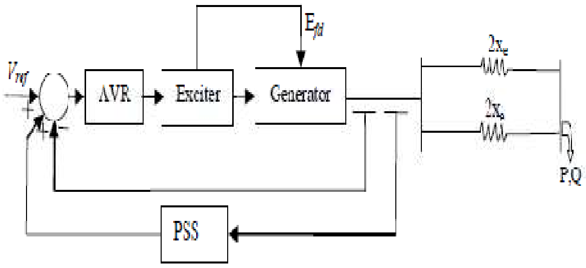

Figure 2: SIMB System

The state variables are defined as follows:

$X = [\Delta\omega \Delta\delta \Delta E_q^{'} \Delta E_{fd}]\ T$

Then a SMIB system can be represented in the following state-space form:

$$\dot{X} = AX + Bu \quad (6)$$

$$y = CX$$

Where

$$X = [\Delta\omega \Delta\delta \Delta E_q^{'} \Delta E_{fd}]\ A = \begin{bmatrix} -\frac{D}{M} & -\frac{K_1}{M} & -\frac{K_2}{M} & 0 \\ \omega_0 & 0 & 0 & 0 \\ 0 & -\frac{K_4}{T_{do}} & -\frac{1}{T_{d0}K_3} & \frac{1}{T_{d0}} \\ 0 & -\frac{K_{AK_5}}{T_A} & -\frac{K_A K_6}{T_A} & -\frac{1}{T_A} \end{bmatrix} \quad (7)$$

$$B = \begin{bmatrix} \frac{1}{M} & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & \frac{K_A}{T_A} \end{bmatrix}, C = [0\ 1\ 0\ 0],\ u = [\Delta T_m \Delta V_{ref}]^T$$

The parameters constants $K1$ to $K6$ represent the system parameters at a certain operation condition [5, 6]. Equation (8) describes the state equations of the system in the presence of PSS.

By considering PSS, Figure 2 can be represented as Figure 3. Recall that a necessary and sufficient condition for the system to be stable is that the eigenvalues of the closed-loop system must be lie in the left hand side of complex s -plane. First of all, the following eigenvalues have been proposed to achieve the least damping of LFO based on LQR scheme by considering PSS [6]. In this project, to achieve the desired performance, we also use these eigenvalues values.

$$\text{eig}_{\text{index}}\ (\hat{A}) = \{-18.62 - 11.6\ -2.155 - 0.987\ \ - 0.3124 \pm j6.96 - 0.102\} \quad (9)$$

Before proceeding with the optimization operations, a performance criterion or an objective function should be first defined. In general, the heuristic algorithm such as PSO only needs to evaluate the objective function to guide its search and no requirement for derivatives about the system. In this study, the sum of ratio between desired eigenvalues and real eigenvalues is considered as fitness. So, the following fitness function is defined.

$$F = \sum_{R=1}^{3} \sum_{i=1}^{7} \frac{\sigma_{desired}(i)}{\sigma(i)} \tag{10}$$

Where $\sigma_{desired}$ and σ is the real part of desired eigenvalues $eig_{desired}$ and eig ($\hat{A}$), respectively.

$$\begin{bmatrix} \Delta\dot{\omega} & \Delta\dot{\delta} & \Delta\dot{E}'_q & \Delta\dot{E}_{fd} & \Delta\dot{N}_1 & \Delta\dot{N}_2 & \Delta\dot{U}_{PSS} \end{bmatrix}^T = \hat{A}.\begin{bmatrix} \Delta\omega & \Delta\delta & \Delta E'_q & \Delta E_{fd} & \Delta N_1 & \Delta N_2 & \Delta U_{PSS} \end{bmatrix}^T$$

$$\hat{A} = \begin{bmatrix} -\frac{D}{M} & -\frac{K_1}{M} & -\frac{K_2}{M} & 0 & 0 & 0 & 0 \\ \omega_0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -\frac{K_4}{T'_{do}} & -\frac{1}{T'_{do}K_3} & \frac{1}{T'_{do}} & 0 & 0 & 0 \\ 0 & -\frac{K_A K_5}{T_A} & -\frac{K_A K_6}{T_A} & -\frac{1}{T_A} & 0 & 0 & \frac{K_A}{T_A} \\ -\frac{D}{M}\frac{T_1}{T_2} & -\frac{K_1}{M}\frac{T_1}{T_2} & -\frac{K_2}{M}\frac{T_1}{T_2} & 0 & -\frac{1}{T_2} & \frac{1}{T_2}-\frac{T_1}{T_2 T_W} & 0 \\ -\frac{D}{M} & -\frac{K_1}{M} & -\frac{K_2}{M} & 0 & 0 & -\frac{1}{T_W} & 0 \\ -\frac{DT_1 K_{PSS} T_3}{M T_2 T_4} & -\frac{K_1 T_1 K_{PSS} T_3}{M T_2 T_4} & -\frac{K_2 T_1 K_{PSS} T_3}{M T_2 T_4} & 0 & \frac{K_{PSS}}{T_4}-\frac{K_{PSS} T_3}{T_2 T_4} & \left(\frac{1}{T_2}-\frac{T_2}{T_2 . T_W}\right)\frac{K_{PSS} T_3}{T_4} & -\frac{1}{T_4} \end{bmatrix} \tag{8}$$

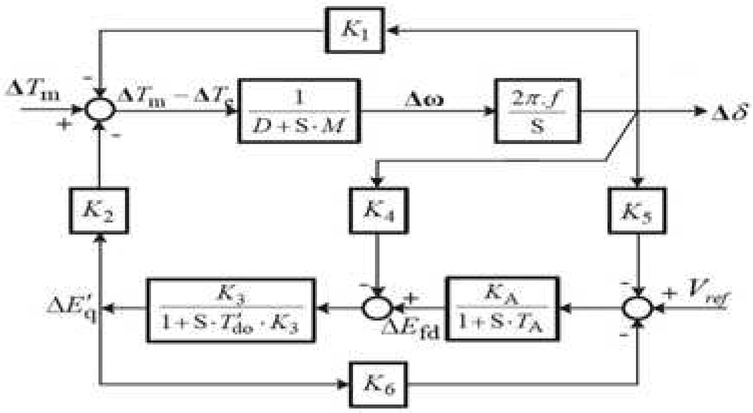

Figure 3: Linearized Model of SMIB System

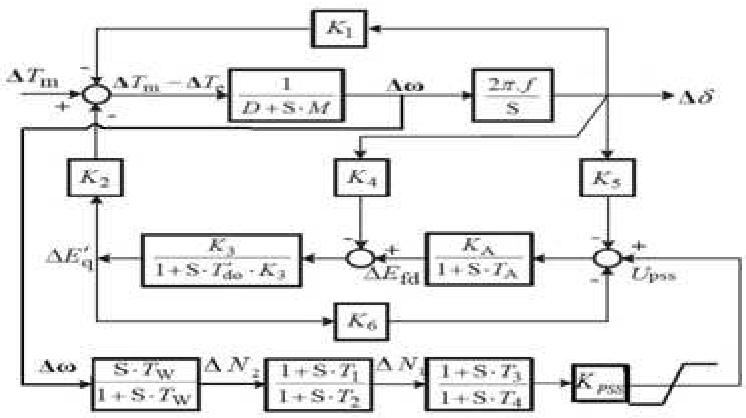

Figure 4: Linearized Model of SMIB System with PSS Attendance

It is noticeable that in order to suitable compare of the corresponding poles, the real part of desired and actual eigenvalues are sorted. In other words, the farthest actual eigenvalue is compared to the farthest desired eigenvalue whereas the nearest actual eigenvalue is compared to the nearest desired eigenvalue. In fact, it confirms that we do not have any unstable eigenvalues.

Now the constraint optimization problem is to find the optimal parameters of PSS (i.e. T_1,T_2,T_3,T_4 and K_{PSS}) whereas the problem constraints are the optimized parameter bounds. Therefore, the design problem can be formulated as the following optimization problem. Minimization *F* subject to

$T_i^{min} \leq T_1 \leq T_i^{max}, K^{min}_{pss} \leq K_{pss} \leq K_{pss}^{max}$

The proposed approach employs IPSO algorithm to solve this optimization problem and search for the optimal set of PSS parameters. The typical ranges of these parameters are:

$0.01 \leq T1 \leq 1.5,\ 0.01 \leq T_3 \leq 1.5,\ 0.001 \leq T_2 \leq 2,$

$0.001 \leq T_4 \leq 2,\ 10 \leq K_{PSS} \leq 50$(11)

SIMULATION RESULTS

This section is devoted to the assessment of proposed scheme. The power system stabilization using the proposed IPSO algorithm is evaluated by comparing with several conventional schemes in different loading regimes. In order to this, simulation results are carried out in five general cases:

Case 1: SMIB without PSS.

Case 2: SMIB with designed PSS based using LQR scheme.

Case 3: SMIB with designed PSS using lead

Controller $G_C = 1.2\frac{1+1.27s}{1+0.092s}$

Case 4: SMIB with designed PSS using CPSO algorithm.

Case 5: SMIB with designed PSS using the proposed IPSO algorithm

The typical ranges of PSS parameters values are summarized in the appendix. Moreover, to cover the wide operating conditions of machine under study, the loading regime is opted as Heavy loading regime

(P = 1.2 $_{p.u.}$, Q = 0.2 $_{p.u.}$)

Hence, the proposed controller is designed based on the regimes. Testing the proposed designed controller is also checked on the different operating conditions. The parameters of controllers are tuned using the PSO algorithms by minimizing the fitness function given in Equation (9). To achieve this, a proper choice of the PSO parameters is required. To perform fair comparison, the same computational effort is used in both of the PSO algorithms. Thereby, the population size and maximum generation are considered as 20 and 100, respectively. Moreover, in both CPSO and IPSO algorithms, we set c_1= c_2=2 and V_{max} and V_{min} are equal to the length of the search space. Furthermore, the inertia weight in CPSO is set to 0.4. After 100 iterations, the optimized PSS parameters values using IPSO algorithm are determined as follows:

T_1=0.05, T_2=0.001, T_3=1.39, T_4=0.001, K_{PSS}=49

Simulation results are shown in Figures 5-12.

Referring to Figures 5-12, it can be concluded the effectiveness of the proposed approach to damp out the electromechanical oscillation and enhance the performance of system in the different loading regimes. Although the results of proposed algorithm is better than CPSO algorithm, but significant advantage of proposed PSO is in terms of convergence speed.

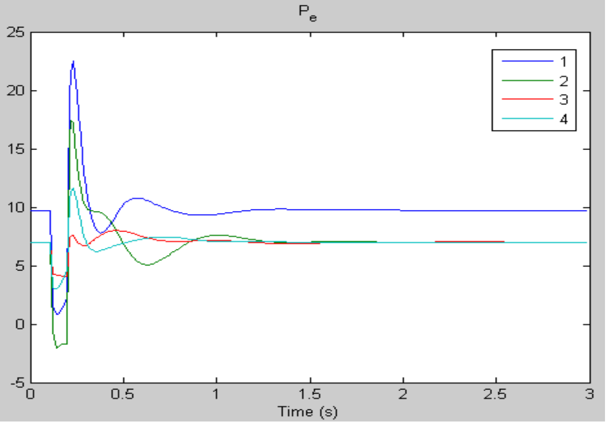

Figure 5: Electrical Power P_e before Optimization

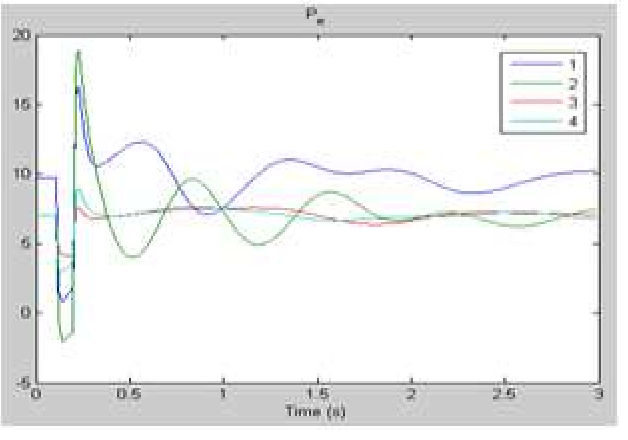

Figure 6: Electrical Power P_e after Optimization

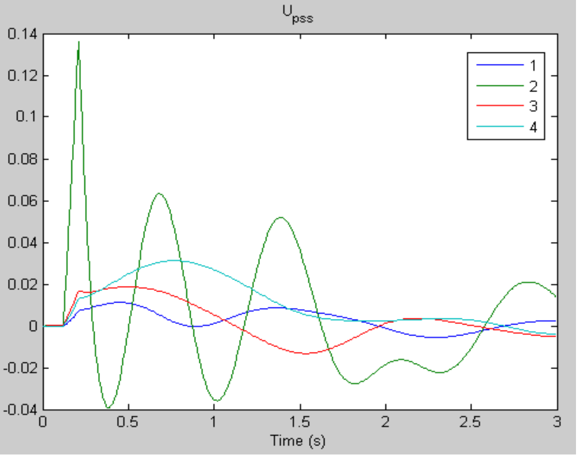

Figure 7: Power System Stability Constant U_{PSS} before Optimization

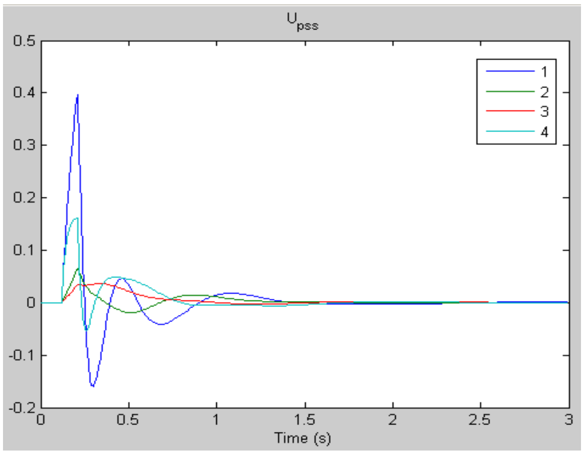

Figure 8: Power System Stability Constant U_{PSS} after Optimization

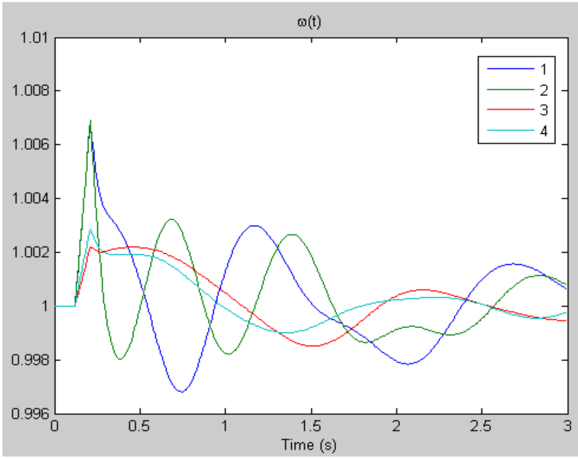

Figure 9: Rotor Speed Variation *Ω* before Optimization

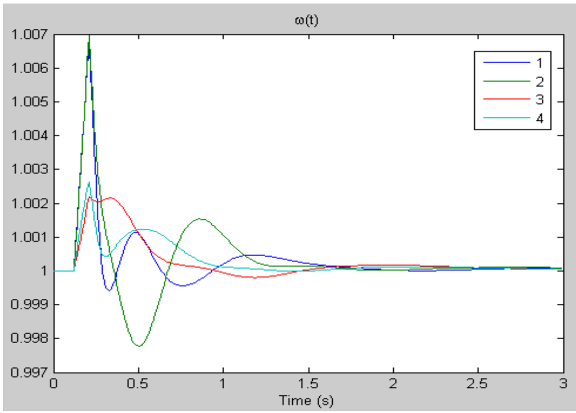

Figure 10: Rotor Speed Variation *Ω* after Optimization

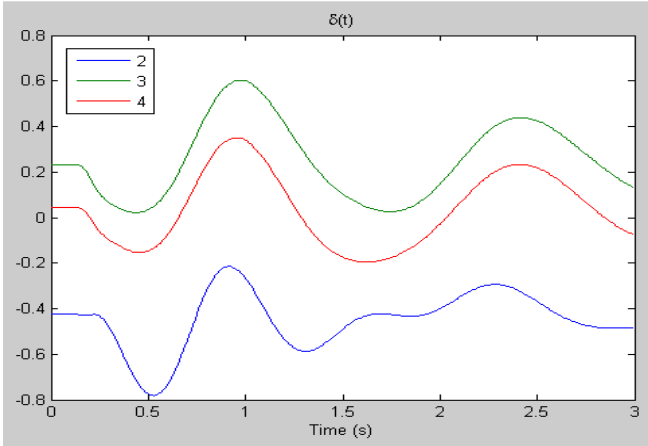

Figure 11: Rotor Angle Variation Δ before Optimization

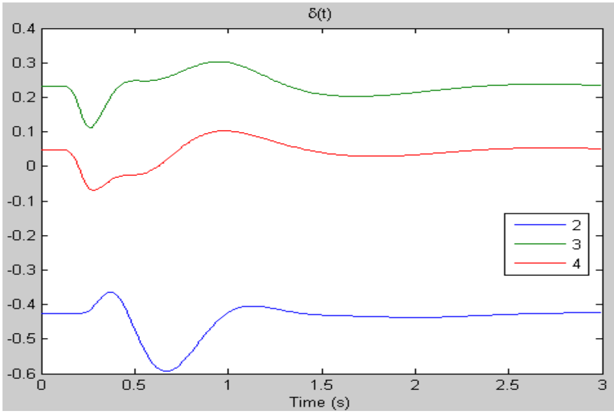

Figure 12: Rotor Angle Variation Δ after Optimization

CONCLUSIONS

The AVR function to regulate voltage can reduce damping torque, the generator's stability limitation and power network. In addition, to eliminating the negative effect of AVR, one can guarantee the network stability by using a feedback from a signal of rotor speed deviations and engaging it in the controlling excitation voltage. This feedback is so-called Power System Stabilizer (PSS) that can improve the stability of network by its proper design and damp the LFO. In this project, the IPSO algorithm was introduced. This proposed IPSO was utilized to find the optimize parameters of PSS for SMIB system by minimizing the fitness function. Using the proposed algorithm, the LFO can be reduced appropriately. The main advantage of proposed algorithm is to achieve faster convergence speed whereas the appropriate performance of system at different loading conditions was guaranteed. Simulation results demonstrated the effectiveness of developed technique

NOMENCLATURES

$$K_1 = C_3 \frac{P^2}{P^2+(Q+C_1)^2} + Q + C_1$$

$$K_2 = C_4 \frac{P}{\sqrt{P^2+(Q+C_1)^2}}$$

$$K_3 = \frac{x_d^{'} + x_e}{x_d + x_e}$$

$K_4 = C_5 \frac{P}{\sqrt{P^2+(Q+C_1)^2}}$

$K_5 = C_4 x_e \frac{P}{V^2+Qx_e}\left[C_6 \frac{C_1+Q}{P^2+(Q+C_1)^2}\right]$

$K_6 = C_7 \frac{\sqrt{P^2+(C_1+Q)^2}}{V^2+Qx_e}\left[x_e + \frac{C_1 x_q (C_1+Q)}{P^2+(Q+C_1)^2}\right]$

$T_{m:}$ Mechanical torque

$T_{e:}$ Electrical torque

$V_{t:}$ Terminal voltage

E_q: Inducted*emf*proportional to field current

E_{fd}: Generator field voltage

V_{ref}: Reference value of generator field voltage

x_d',x_d,x_q: Generator, d-axis and q-axis synchronous reactances, respectively.

x_e: Line reactance

V: Infinite bus bar voltage

T_{do}': Open circuit direct-axis transient time constant

M: Inertia coefficient

D: Damping factor

K_A, *TA*: AVR and exciter gain and time constant, respectively

x_e=0.4,x_q=1.55,x_d=1.6,x_d' =0.32, V =1, f =50Hz,T_{do}' =6sec, M =10, T_A=0.05sec, K_A=25, D =0

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