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Load Frequency Control in Interconnected Power System Using Multi-Objective PID Controller

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Abstract: In this study, designing of multi-objective (MO) proportional, integral and derivative (PID) controller for load frequency control (LFC) based on adaptive weighted particle swarm optimization (AWPSO) has been proposed. Unlike single objective optimizations methods, MO optimization can find different solutions in a single run and we can select appropriate and desirable solution based on valuation to the objects. In this study for PID controller design, overshoot/undershoot and settling time are used as objective functions for MO optimization in LFC problem. So that various solutions with different overshoot/undershoot and settling time obtained. From these different PID parameters, one can select a single solution based on valuation to objects and as well as system constraints, reliability etc. The proposed method is used for designing of PID parameters for two area interconnected power system. From the simulation results, efficiency of proposed controller design can be seen.

Key words: Multi-objective particle swarm optimization, load frequency control, PID controller, power system control

INTRODUCTION

One of the principle aspect of Automatic Generation Control (AGC) of power system is the maintains of frequency and power change over the tie-lines at their scheduled values. Therefore, it is a simultaneous load frequency control (LFC) (Saadat, 2002). In LFC problem, each area has its own generator or generators and it is responsible for its own load and scheduled interchanges with neighboring areas. The tie-lines are utilities for contracted energy exchange between areas and provide inter-area support in abnormal conditions. Area load changes and abnormal conditions lead to mismatches in frequency and scheduled power interchanges between areas. These mismatches have to be corrected by LFC, which is defined as the regulation of the power output of generators within a prescribed area (Kumar, 1997). Therefore, the LFC task is very important in interconnected power systems. It is well known that power systems are nonlinear and complex, where the parameters are a function of the operating point and the loading in power system is never constant. Over the past decades, many techniques have been developed for the LFC problem. A number of state feedback controllers based on linear optimal control theory, robust and conventional adaptive controller have been proposed to achieve better performance (Aldeen and Trinh, 1994; Pan and Liaw, 1989; Zribi *et al*., 2005; Bevran and Hiyama, 2008; Shayeghi, 2008a). state adaptive controllers (Kazemi *et al*., 2003) involve large computational burden and time. Also, Most of proposed techniques were based on the classical proportional and integral (PI) or proportional, integral and derivative (PID) controllers. Its use is not only for their simplicities, but also due to its success in a large number of industrial applications. In Classical methods, such as Ziegler-Nichols and Cohen-Coon, these controllers are tuned based on trial-error approaches and, therefore, have not good performance. To achieve optimal gains for PID controller, Genetic Algorithm (GA) or Particle Swarm Optimization (PSO) methods were addressed (Ghoshal and Goswami, 2003; Ghoshal, 2004; Talaq and Al-Basri, 1999; Abdennour, 2002; Shayeghi, 2007, 2008b; Mukherjeea and Ghoshal, 2008). In mentioned study for LFC problem, the area control error (ACE), which composed of frequency and tie-line error, was defined as fitness for PSO and GA. Moreover, in these studied, after obtaining PI/PID gains for some operating point of power system, adaptive fuzzy

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gain scheduling technique was proposed. However, the most of real-world control problems refer to multi-objective control designs that controller must follow several objectives such as stability, disturbance attenuation and reference tracking with considering of practical constraints, simultaneously. For this reasons, in this study Multi-Objective Particle Swarm Optimization (MOPSO) is used for tuning of PID controller parameters for LFC in interconnected power system. Unlike classical methods such as Ziegler-Nichols and Cohen-Coon (Astrom and Wittenmark, 1997) and single objective optimization methods such as GA (Abdennour, 2002; Shayeghi, 2007; Goldberg, 1989; Demiroren and Zeynelgil, 2007) and PSO (Ghoshal, 2004; Shayeghi, 2008b), the MO optimization can minimize some important aspect of a system such as overshoot/undershoot and settling time simultaneously. So that various solutions with different overshoot/undershoot and settling time obtained. From these different PID Parameters, one can select a single solution based on valuation to objects and as well as system constraints, reliability etc. For example, in such cases overshoot/undershoot has more importance than setting time and vice versa.

MATERIALS AND METHODS

A two area interconnected power system model: A two-area system consists of two single areas connected through a power line called the tie-line. Each area feeds its user pool and the tie-line allows electric power to flow between areas. Since both areas are tied together, a load perturbation in one area affects the output frequencies of both areas as well as the power flow on the tie-line. The control system of each area needs information about the transient situation of both areas in order to brings the local frequency back to its steady state value. Information about the other areas found in the output frequency fluctuation of that area and in the tie-line power fluctuation. Therefore, the tie-line power is sensed and the resulting tie-line power signal is fed back into both areas (Ertugrul and Kocaarslan, 2005a , b; Yesil and Eksin, 2004). Frequency control is accomplished by two different control actions in interconnected two area power systems: primary speed control and supplementary or secondary control actions. The primary speed control makes the initial coarse readjustment of the frequency. By its actions, the various generators in the control area track a load variation and share it in proportion to their capacities. The speed of the response is limited only by the natural time lags of the turbine and the system itself. The supplementary speed control takes over the fine adjustment of the frequency by resetting the frequency error to zero through an integral action. Schematic of two-area interconnected power system for the uncontrolled case is shown in Fig. 1. The overall system can be modeled as multi-variable system in the following from:

$$\dot{x} = Ax(t) + Bu(t) + Ld(t) \tag{1}$$

where, A, B and L are the system matrix, input and disturbance distribution matrices, respectively, x(t), u(t) and d(t) are the state, control and load changes disturbance vectors, respectively and represented as:

$$\begin{aligned} x(t) &= [\Delta f_1 \ \ \Delta P_{g1} \ \ \Delta P_{v1} \ \ \Delta P_{tie} \ \ \Delta f_2 \ \ \Delta P_{g2} \ \ \Delta P_{v2}]^T \\ d(t) &= [\ \Delta P_{d1} \ \ \Delta P_{d2}]^T \\ u(t) &= [u_1 \quad u_2\ ]^T \end{aligned} \tag{2}$$

where, Δ denotes deviation from the nominal values. u_1 and u_2 are the control outputs in Fig. 1. The system output, which depends on the Area Control Error (ACE) shown in Fig. 1 and represented as:

$$y(t) = \begin{bmatrix} y_1(t) \\ y_2(t) \end{bmatrix} = \begin{bmatrix} ACE_1 \\ ACE_2 \end{bmatrix} = Cx(t) \tag{3}$$

$$ACE_i = \Delta p_{yie,\,I} + b_i \Delta f_i \tag{4}$$

where, b_i is the frequency bias constant, Δf_i is the frequency deviation and $\Delta P_{tie,i}$ is the change in tie-line power for the i-th area and C is the output matrix.

Basic PSO and AWPSO: The PSO algorithm is a population based search algorithm based on the simulation of the social behavior of birds within a flock. In PSO, individuals referred to as particles, are flown through hyper dimensional search space. Changes to the position of particles within the search space are based on the social psychological tendency of individuals to emulate the success of other individuals. The changes to a particle within the swarm are therefore influenced by the experience or knowledge, of its neighbors. The search behavior of a particle is thus affected by that of other particles within the swarm (PSO is therefore a kind of symbiotic cooperative algorithm). The consequence of modeling this social behavior is that the search process is such that particles stochastically return toward previously successful region in the search space (Engelbrecht, 2006). A swarm consists of a set of particles, where each particle represents a potential solution. Particles are then flown through the hyperspace, where the position of each particle is changed according to its own experience and that of its neighbors. Let $\vec{x}_i(t)$ denotes the position of particle P_i in hyperspace, at time step t. The position of P_i is then changed by adding a velocity $\vec{v}_i(t)$ to the current position as:

$$\vec{x}_i(t) = \vec{x}_i(t-1) + \vec{v}_i(t) \qquad (5)$$

The velocity vector drives the optimization process and reflects the socially exchange information. Velocity update equation is as follows:

$$\vec{v}_i(t) = w\vec{v}_i(t-1) + c_1 r_1(\vec{P}_{bi} - \vec{x}_i(t-1)) + c_2 r_2(\vec{P}_g - \vec{x}_i(t-1)) \qquad (6)$$

where, w is the inertia weight, c_1 and c_2 are positive constants and r_1 and r_2 are random numbers obtained from a uniform random distribution function in the interval [0, 1]. The parameters $\vec{P}_{bi}$ and $\vec{P}_g$ represent the best previous position of the i-th particle and position of the best particle among all particles in the population respectively (Engelbrecht, 2006). The inertia weight controls the influence of previous velocities on the new velocity. Large inertia weights cause larger exploration of the search space while smaller inertia weights focus the search on a smaller region. Typically, PSO started with a large inertia weight, which is decreased over time. Shi and Eberhart (2001) proposed a 'fuzzy adaptation' of the inertia weight due to the fact that a linearly-decreasing weight would not be adequate to improve the performance of the PSO due to its non-linear nature. In this study, we use the following formula to change the inertia weight at each generation:

$$w = w_0 + r(1-w_0) \qquad (7)$$

where, w_0 is the initial positive constant in the interval [0, 1] and r is random number obtained from a uniform random distribution function in the interval [0, 1]. The suggest range for w_0 is [0, 0.5], which make the weight w randomly varying between w_0 and 1.

To improve the performance of the PSO for MO optimization problems, Mahfouf *et al.* (2004) proposed an Adaptive Weighted PSO (AWPSO) algorithm, in which the velocity in Eq. 6 is modified as follows:

$$\vec{v}_i(t) = w\vec{v}_i(t-1) + \alpha\left[c_1 r_1(\vec{P}_{bi} - \vec{x}_i(t-1)) + c_2 r_2(\vec{P}_g - \vec{x}_i(t-1))\right] \qquad (8)$$

The second term in Eq. 8 can be viewed as an acceleration term, which depends on the distances between the current position $\vec{x}_i(t)$, the personal best $\vec{P}_{bi}$ and the global best $\vec{P}_g$.

The acceleration factor α is defined as follows:

$$\alpha = \alpha_0 + t/T \qquad (9)$$

where, t is the current generation, T denotes the number of generations and the suggest range for α_0 is [0.5, 1]. As can be seen from Eq. 8, the acceleration term will increase as the number of iterations increases, which will enhance the global search ability at the end of run and help the algorithm to jump out of the local optimum, especially in the case of multi-modal problems. One of the simplest approaches to deal with MO problems is to define an aggregate objective function as a weighted sum of the objectives. Single objective optimization algorithms can then be applied, without any changes to the algorithm, to find optimum solutions. We use an aggregation approach to construct the evaluation function Eval for MO optimization as follows (Engelbrecht, 2007).

$$\mathrm{Eval}(k) = \sum_{i=1}^{n} w_i f_i(k); \quad \sum_{i=1}^{n} w_i = 1 \qquad (10)$$

where, n is the number of objective functions and k denotes the k-th particle and the weights w_i for each objective are changed and normalized as follows:

$$w_i = \frac{\mu_i}{\sum_{j=1}^{n} \mu_j}; \quad \mu_i, \mu_j \in U(0, 1) \qquad (11)$$

where, μ_i and μ_j are random numbers obtained from a uniform random distribution function in the interval [0, 1].

Multi-objective design of PID controller

Outline: It is well known that the PID controller is the most popular approach for industrial process control, such as LFC problem and several design techniques have been developed. In LFC problem, by taking ACE as the system output, the control vector for a PID controller in continuous form can be given as:

$$u_i = -(K_P ACE_i + K_D \dot{ACE}_i + K_I \int ACE_i) \qquad (12)$$

where, the K_P, K_D and K_I are the proportional, derivative and integral gains. In classical methods, there are some approaches for tuning of PID controller parameters (i.e., Ziegler-Nichols and Cohen-Coon). In these methods, process, in response to unit step, has been modeled as a following transfer function:

$$G_p = \frac{k_p}{1+sT} e^{-sL} \qquad (13)$$

where, k_p, L and T are the gain, delay time and constant time of process, respectively. After this modulation, according to the determined table, Ziegler-Nichols and Cohen-Coon tables, the PID parameters are achieved. The application of these methods for PID design have been restricted for large scale and complicated system due to, lack of accuracy and its cumbrous. Also, population based techniques (i.e., GA and PSO) have been used for designing of optimal PID controller parameters. In these approaches the gains of PID controller, are searched in feasible region of response until a determined cost function minimized. In design of PID controller parameters, it is desirable that controlled system include suitable transient and steady state response. So, some specific feature of system such as overshoot/undershoot, settling time and rise time must be improved. Therefore, this design can be mentioned as a MO optimization problem.

Fitness functions: For the general control problem, the optimization of different number of systems performances is desired. The following simultaneous performance specifications (the objectives) are adopted in this study:

- Overshoot/Undershoot minimization:

$$f_1(K_I, K_P, K_D) = \max\left(\frac{1}{1+OU}\right) \tag{14}$$

- Settling time minimization:

$$f_2(K_I, K_P, K_D) = \max\left(\frac{1}{1+T_N}\right) \tag{15}$$

where, OU is the average overshoot or undershoot of areas and T_N is defined as follows:

$$T_N = \frac{T_{Settlingtime}}{T_{Total}} \tag{16}$$

where, $T_{settling\ time}$ and T_{Total} are the average settling time of areas and final simulation time, respectively. In fact, the T_{Total} is used for normalization of settling time object. Here, aggregation based MO PSO is used to maximize these two objective functions in order to minimizing overshoot/undershoot and settling time simultaneously. That is must be mentioned the ACEs signals in each area for Overshoot/undershoot and settling time minimization is handled and the same PID controllers for areas are designed.

RESULTS AND DISCUSSION

In this study, the nominal parameters of two area interconnected power system that has been used in the simulation are considered as follow:

$T_g = 0.08s$, $T_{12} = 0.545pu$, $T_t = 0.3s$, $T_p = 20s$, $k_p = 120Hz/pu$, $R = 2.4\ Hz/pu$ and $b = 0.425Hz/pu$

where, the power system time constant, T_p, synchronizing power coefficient, T_{12} and frequency bias setting b may be changed according to different operating point of the power system.

The block diagram of controlled system for i-th area is depicted in Fig. 2. For MO optimization of PID parameters we set $w_0 = 0.15$, $\alpha_0 = 0.5$, the population size N = 30 and the number of iteration T = 50. In addition, aggregation-based method is used for MO PSO. In order to demonstrate the effectiveness of the proposed method, some simulations were performed. In addition, a nonlinear model of Fig. 3 (with ±0.015 limits) replaces the linear model of a nonreheating turbine in Fig. 1. This is to take into account the generating constraint (GRC), i.e., the practical constraint on the response speed of a turbine.

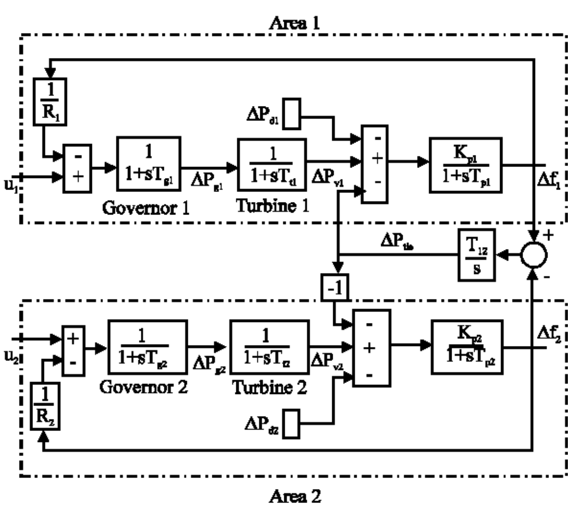

Fig. 1: The two-area interconnected power system used in this study

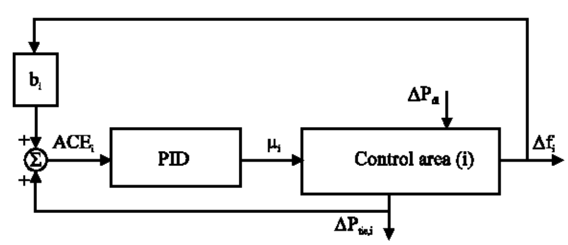

Fig. 2: PID controller installed for i-th area

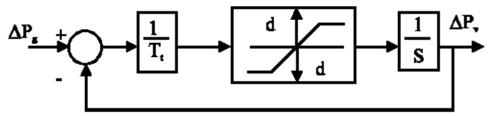

Fig. 3: Nonlinear turbine model with GRC

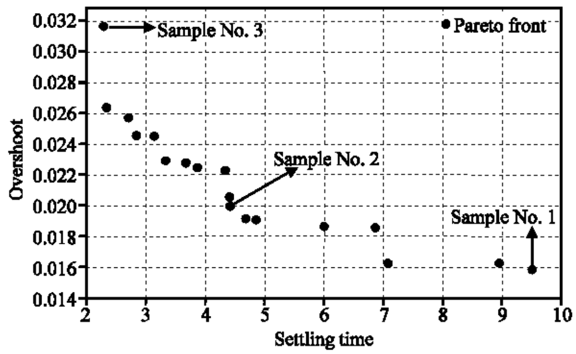

Fig. 4: Pareto front for case 1

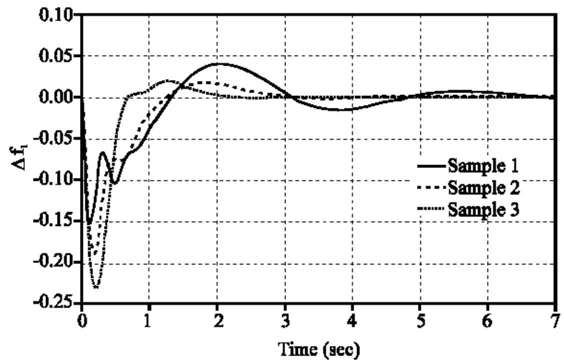

Fig. 5: Frequency deviation of three samples in first area for case 1

Case 1: In this case, the system performance with nominal parameters is tested. The nominal parameters are set as above and apply large load demands of $\Delta p_{d1}(t) = 0.15$ p.u. and $\Delta p_{d2}(t) = 0.10$ p.u. MW to first and second area, respectively. The obtained Pareto front after deleting dominated solutions is shown in Fig. 4. The response of Δf_1 and Δf_2, for three selected samples (sample No. 1~3) from Pareto front are shown in Fig. 5 and 6, respectively.

The PID gains for mentioned three samples in case 1 are shown in Table 1. These three samples and clearly other samples in Pareto front, have different PID gains, which causes we have different undershoot and settling time for frequency deviations in areas. In fact, the proposed MO optimization method gives a number of solutions for PID design problem in LFC. Therefore, we can choose appropriate gains based on valuation to undershoot/overshoot and settling time as well as system

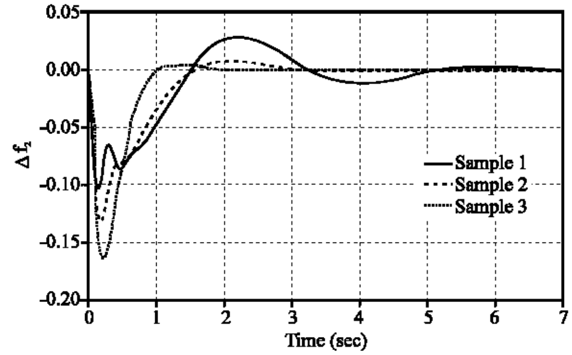

Fig. 6: Frequency deviation of three samples in second area for case 1

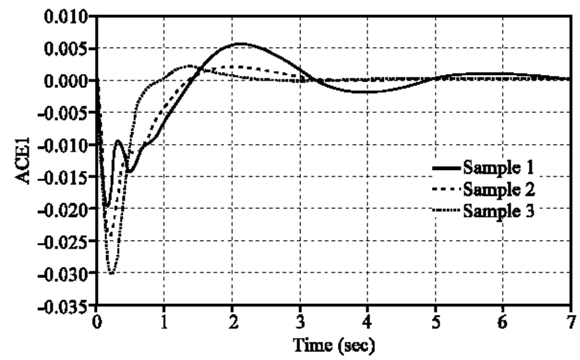

Fig. 7: ACE signal of three samples (Three PID) in first area (case 1)

Table 1: PID gains for three samples in Pareto front, case 1 and 2

Case		K_P	K_I	K_D
Case 1	Sample#1	2.1004	0.1743	4.8013
	Sample#2	4.3418	0.1936	3.3000
	Sample#3	4.8145	0.1767	1.8615
Case 2	Sample#1	3.4207	0.0750	3.5482
	Sample#2	4.0462	0.3139	2.0825
	Sample#3	4.9385	0.2456	1.7101

constraint, reliability etc. for example, it is clear the PID parameters which remarked by Sample No. 1 have the smallest and largest undershoot and settling time of others, respectively.

Also, the ACE signals for three mentioned samples at two areas are shown in Fig.7 and 8, respectively.

Case 2: In this case the other nominal operation conditions parameters which (T_p = 30, T_{12} = 0.545, b = 0.125) are used for two area and apply load changes of $\Delta p_{d1}(t) = -0.10$ and $\Delta p_{d2}(t) = 0.15$ p.u. MW to first and second areas, respectively. The obtained Pareto front is shown in Fig. 9. The response of Δf_1 and Δf_2, for three selected samples from Pareto front are shown in Fig. 10 and 11, respectively. In addition, the ACE for three

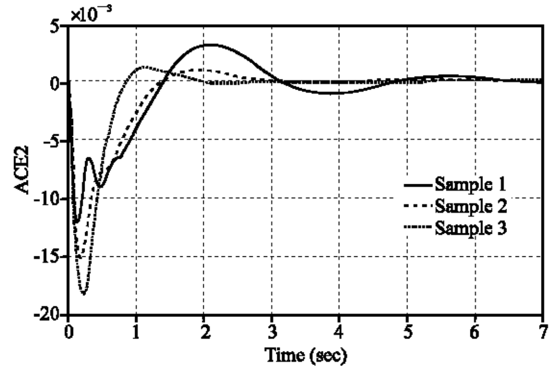

Fig. 8: ACE signal of three samples (Three PID) in second area (case 1)

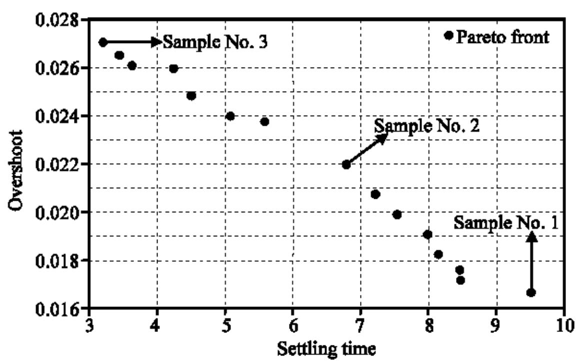

Fig. 9: Pareto front for case 2

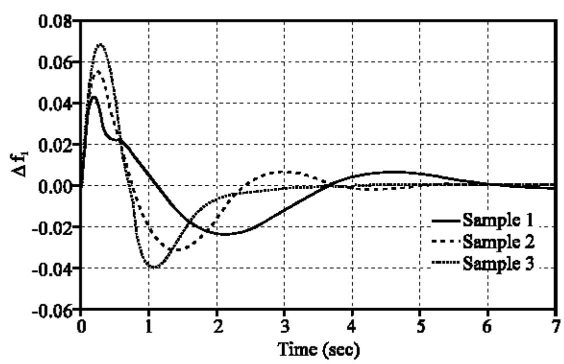

Fig. 10: Frequency deviation of three samples in first area for case 2

samples at two areas is shown in Fig. 12 and 13, respectively.

The Fig. 12 and 13 show choosing solutions from different parts of Pareto front, cause to different results from the aspect of overshoot/ undershoot and settling time. So one can select a single solution based on system conditions for PID parameters. The obtained PID gains for three samples are given in Table 1.

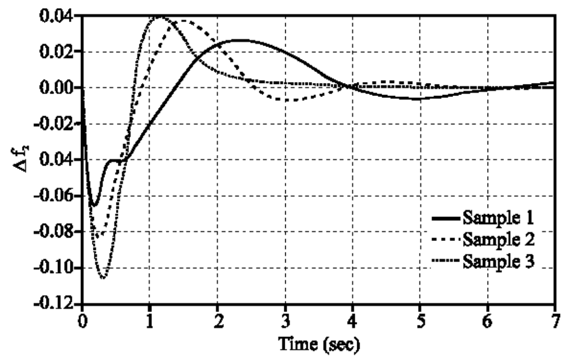

Fig. 11: Frequency deviation of three samples in second area for case 2

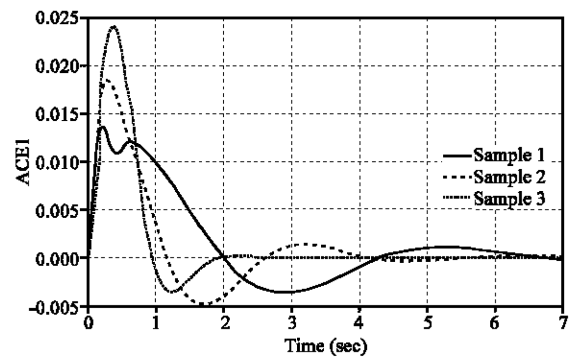

Fig. 12: ACE signal of three samples (Three PID) in first area (case 2)

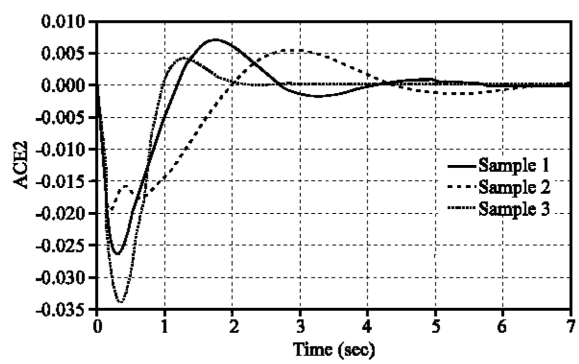

Fig. 13: ACE signal of three samples (Three PID) in second area (case 2)

CONCLUSION

In this study, designing of PID parameters with multi-objective AWPSO for LFC in interconnected power system has been proposed. Two-area power system is used as a test system to demonstrate the effectiveness of the proposed methods under various operating conditions and area load demand. In this method more than one PID design for each of operating point obtained, so one can select a single solution based on system constraints, overshoot/undershoot and settling time. After selecting appropriate PID gains from Pareto front, we can use an adaptive fuzzy gain-scheduling scheme for tuning off-nominal operating points.

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