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

A. Sharifi, K. Sabahi, M. Aliyari Shoorehdeli, M.A. Nekoui, M. Teshnehlab

***Abstract*— In this paper designing of multi-objective PID controller for load frequency control (LFC) based on adaptive weighted particle swarm optimization (AWPSO) has been proposed. Conventional methods such as Ziegler-Nichols and Cohen-Coon are based on trial-and-error and their best performances are achieved for first-order process. Single-objective population based methods such as genetic algorithm (GA) and particle swarm optimization (PSO) have only one solution in a single run. Unlike single objective methods, multi-objective optimization can find different solutions in a single run. In the proposed method, overshoot/undershoot and settling time are used as objective functions for multi-objective optimization. The proposed method is used for designing of PID parameters for two area interconnected power system.**

***Keywords*— Multi-objective particle swarm optimization, Load frequency control, PID controller.**

I. 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) [1]. 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 [2]; 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 [2]-[17]. Most of these techniques were based on the classical proportional and integral (PI) or proportional and integral, derivative (PID). Its use is not only for their simplicities, but also due to its success in a large number of industrial applications. These controllers are tuned based on trial-error approaches, there for have large frequency deviations. A number of state feedback controllers based on linear optimal control theory, have been proposed to achieve better performance [3], [4].

In this study multi-objective particle swarm optimization (MOPSO) is used for tuning of non-linear PID controller parameters for LFC in interconnected power system. Unlike classical methods such as Ziegler-Nichols and Cohen-Coon [18] and single objective optimization methods such as GA [23] and PSO [24], multi-objective 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 system constraints, reliability and etc. For example, in such cases overshoot/undershoot has more importance than setting time and vice versa.

II. A Two Area Interconnected Power System Model

Schematic of two area interconnected power system for the uncontrolled case is shown in Fig. 1. Where D denotes deviation from the nominal values and f_i is the system frequency (Hz), R_i is regulation constant (Hz per unit), T_{gi} is speed governor time constant (s), T_{ti} is turbine time constant (s), T_{pi} is power system time constant (s) and D_{pti} is load demand increment. 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:

$$\begin{aligned} x(t) &= [\Delta f_1 \;\; \Delta P_{\sigma 1} \;\; \Delta P_{V1} \;\; \Delta P_{tie} \;\; \Delta f_2 \;\; \Delta P_{\sigma 2} \;\; \Delta P_{V1}]^T \\ d(t) &= [\Delta P_{d1} \;\; \Delta P_{d2}]^T \\ u(t) &= [u_1 \;\; u_2]^T \end{aligned} \tag{2}$$

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Arash Sharifi is with the Department of Computer Engineering, Islamic Azad University Science and Research Branch, Tehran, Iran, (email: Arash.Sharifi@gmail.com)

Kamel Sabahi, Mahdi Aliyari Shoorehdeli, Mohammad Ali Nekoui and Mohammad Teshnehlab are with the Electrical Engineering Department of K.N. Toosi, University of Technology, Tehran, Iran, (email: Kamel_Sabahi@ee.kntu.ac.ir, Aliyari@ieee.org, Manekoui@eetd.kntu.ac.ir Teshnehlab@eetd.kntu.ac.ir)

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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:

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

$$ACE_i = \Delta P_{tie,i} + b_i \Delta f_i \tag{4}$$

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[11].

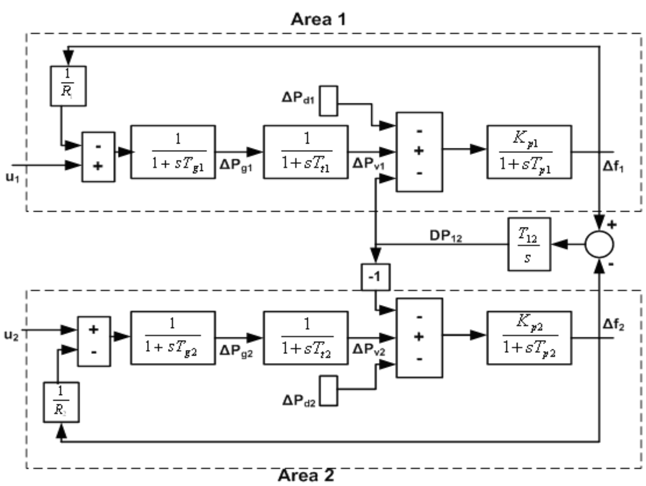

Fig. 1. The two area interconnected power system used in this study.

III. BASIC PSO AND AWPSO

The particle swarm optimization 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 hyperdimensional 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 [19].

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:

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

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

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

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 [19].

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 proposed a 'fuzzy adaptation' of the inertia weight [20] due to the fact that a linearly-decreasing weight would not be adequate to improve the performance of the PSO due to its nonlinear nature. In this paper we use the following formula to change the inertia weight at each generation:

$$w = w_0 + r(1 - w_0) \tag{7}$$

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 multi-objective optimization problems, Mahfouf [21] proposed an Adaptive Weighted PSO (AWPSO) algorithm, in which the velocity in Eq. (6) is modified as follows:

$$\begin{aligned} \vec{v}_i(t) = {} & w\vec{v}_i(t-1) + \alpha\big[c_1 r_1 (\vec{P}_{bi} - \vec{x}_i(t-1)) + \\ & c_2 r_2 (\vec{P}_g - \vec{x}_i(t-1))\big] \end{aligned} \tag{8}$$

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:

$$\alpha = \alpha_0 + t / T \tag{9}$$

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 Equation (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 multi-objective problems (MOPs) 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 multi-objective optimization (MOO) as follows [22]:

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

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:

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

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

IV. Multi-objective Design of PID Controller

A. Outline

It is well known that the PID (proportional integral derivative) controller is the most popular approach for industrial process control and many design techniques have been developed. In classical methods, there are some approaches for tuning of PID controller parameters (i.e. Ziegler-Nichols and Cohen-Coon [18]). In these methods process, in response to unit step, has been modeled as a following transfer function:

$$G_p = \frac{k_p}{1 + sT} e^{-sL} \tag{12}$$

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 mentioned 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 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, this design can be mentioned as a multi-objective optimization problem.

B. 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 work:

1) Overshoot/Undershoot minimization:

$$f_1(K_I, K_P, K_D) = \max \left(\frac{1}{1 + OU} \right) \tag{13}$$

2) Settling time minimization:

$$f_2(K_I, K_P, K_D) = \max \left(\frac{1}{1 + T_N} \right) \tag{14}$$

where OU is the max (overshoot, undershoot) and T_N is defined as follows:

$$T_N = \frac{T_{Settling\ time}}{T_{Total}} \tag{15}$$

Here, aggregation based multi-objective particle swarm optimization is used to maximize these two objective functions in order to minimizing overshoot/undershoot and settling time simultaneously.

V. Simulation and Results

In this study, the nominal parameters of two area interconnected power system that has been used in the simulation are given in Table I. In this table 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 [15].

TABLE I
PARAMETERS OF A TWO AREA MODEL

Operating Conditions			
$\mathbf{T_g}$	**R**	$\mathbf{T_t}$	$\mathbf{k_p}$
0.08 s	2.4 Hz/pu	0.3 s	120 Hz/pu
$\mathbf{T_p}^*$	$\mathbf{T_{12}}^*$	$\mathbf{b}^*$	
10 s	0.145 pu	0.125 Hz/pu	

* These parameters vary, according to the operating condition

The block diagram of controlled system for i-th area is depicted in Fig. 2. For multi-objective optimization of PID parameters we set w_0=0.15, α_0=0.5, the population size N=30 and the number of iteration T=50. Also aggregation based method is used for PSO-MOO.

Case 1: In this case the system performance with nominal parameters is tested. The nominal parameters are set as given in Table I and apply load changes of $\Delta P_{d1}(t)=0.010$ p.u. and $\Delta P_{d2}(t)=-0.010$ p.u. MW to first and second area. The obtained Pareto front after deleting dominated solutions is shown in Fig. 3. The response of Δf_1 and Δf_2, for three selected samples from Pareto front are shown in Fig. 4 and Fig. 5 respectively.

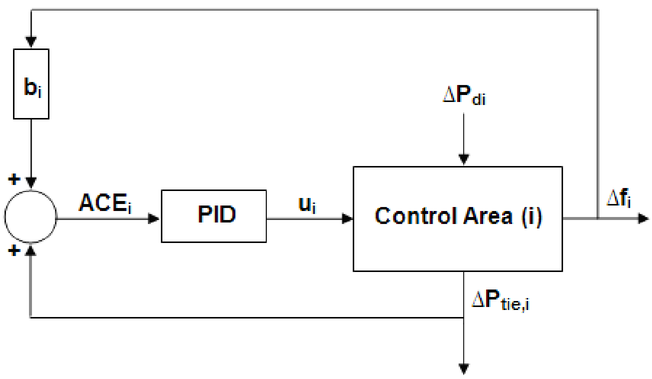

Fig. 2. PID controller installed for *i*-th area.

Case 2: In this case the other nominal operation conditions parameters which ($T_p=20$, $T_{12}=0.345$, $b=0.425$) are used for two area and apply load changes of $\Delta P_{d1}(t)=0.010$ and $\Delta P_{d2}(t)=0.015$ p.u. MW to first and second areas. The obtained Pareto front is shown in Fig. 6. The response of Δf_1 and Δf_2, for three selected samples from Pareto front are shown in Fig. 7 and Fig. 8 respectively.

The figures 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.

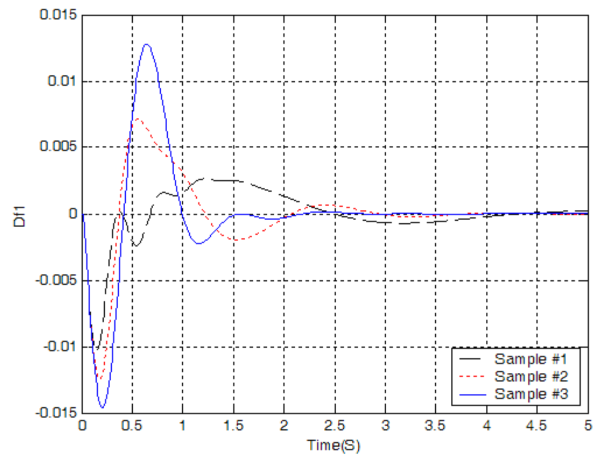

Fig. 4. Frequency deviation of three samples in first area for case 1

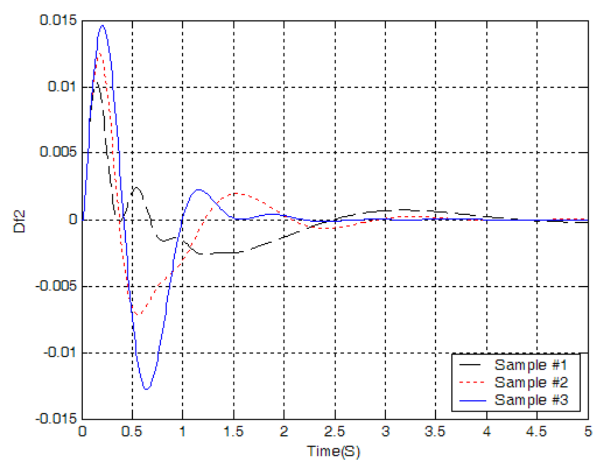

Fig. 5. Frequency deviation of three samples in second area for case 1

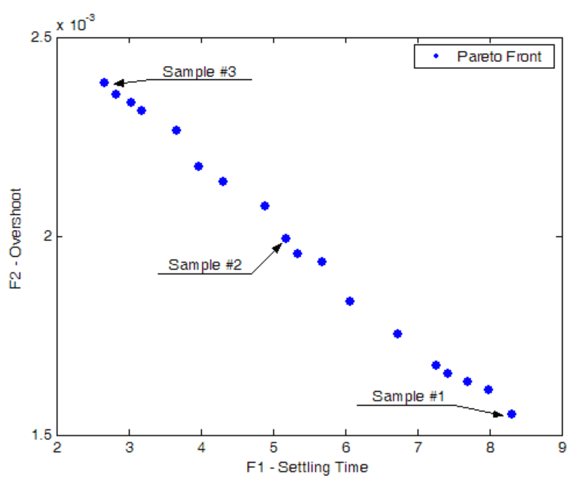

Fig. 3. Pareto front for case 1

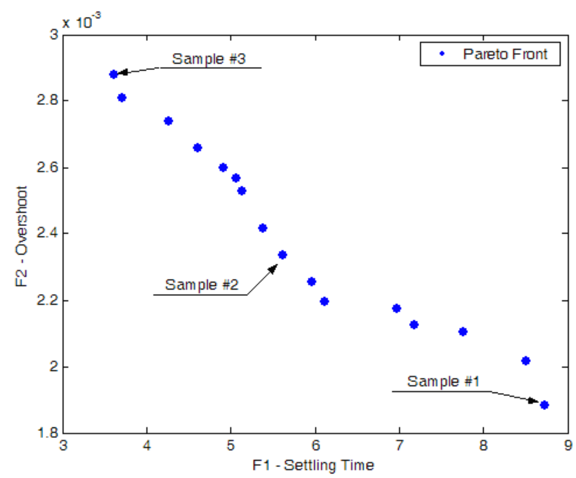

Fig. 6. Pareto front for case 2

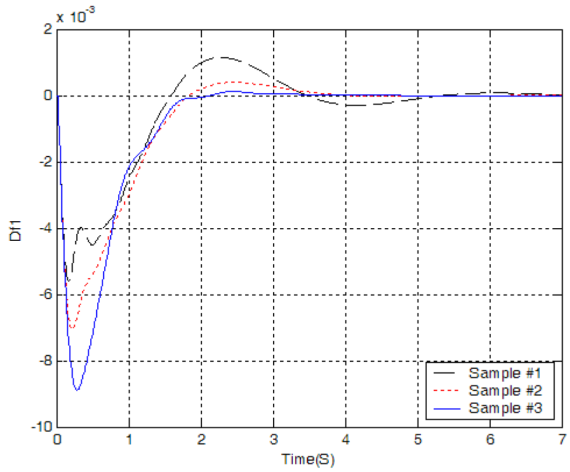

Fig. 7. Frequency deviation of three samples in first area for case 2

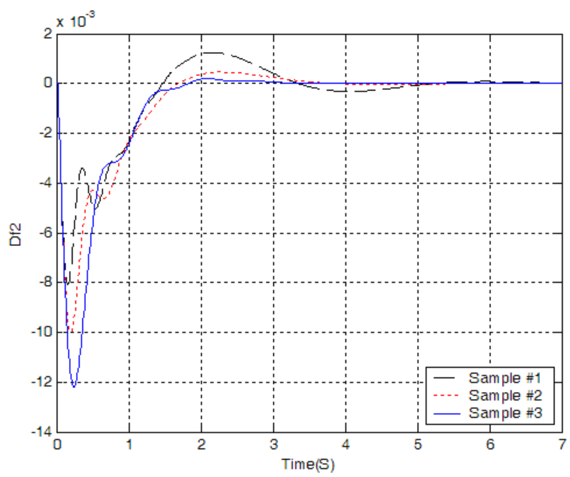

Fig. 8. Frequency deviation of three samples in second area for case 2

VI. 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. As future work, using of an adaptive fuzzy gain scheduling scheme for tuning off-nominal operating points can be suggested.

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