A Swarm Optimization Based Load Frequency Control Application In A Two Area Thermal Power System

Haluk Gözde[1], M.Cengiz Taplamacıoğlu[2], İlhan Kocaarslan[3]

[1, 2] Gazi University Electrical&Electronics Engineering Department, Ankara, Turkey
halukgozde@gmail.com, taplam@gazi.edu.tr
[3] İstanbul University Electrical&Electronics Engineering Department, İstanbul, Turkey
ikocarslan@yahoo.com

Abstract

In this paper, a swarm optimization based optimal proportional-plus-integral (PI) controller is designed for load frequency control (LFC) of a two area thermal power system with governor dead-band. The design is determined an optimization problem and a novel cost function is derived for increasing the performance of convergence to the solution. To optimize the parameters of the cost functions and the PI-controller, the craziness based particle swarm optimization (CRAZYPSO) algorithm is used. The results show that the proposed control method is provided better performance for dynamic responses of the power system.

1. Introduction

In interconnected power systems, a nominal system frequency depends on a balance between produced and consumed real power. A real power inequality in which occurs anywhere of the system is perceived in a whole network as a frequency deviation. Nevertheless, if it is taken into consideration that the properly working of industrial loads connecting to the power system depends on quality of electric energy, this balance is had to keep for holding the steady-state frequency error between acceptable values. The balance of real power in an interconnected power system is provided by the amount of production of the synchronous generators connected to the system is made sense for frequency deviations. If the amount of produced power is less than the demanded one, the speed and also frequency of the generators decrease, and vice versa. For bringing frequency deviation to desired level back is provided by control of the turbines which turn the generators. For this purpose, the PI-controller is classically used, and by tuning the controller gains, the steady-state error of the system frequency is minimized [1, 2].

However, due to the complexity of the power systems such as nonlinear load characteristics and variable operating points, the PI-controllers tuning with conventional methods may be unsuitable in some operating conditions. In literature, some different control strategies have been suggested based on the digital, self-tuning, adaptive, variable structure systems and intelligent/soft computing control [3]. Recently, different PSO based controllers are commonly used in literature as a self-tuning control strategy for LFC [4].

In this study, a craziness based PSO algorithm is used to optimizing the PI-controller gains for load frequency control of a two area thermal power system including governor dead-band. To obtain the best convergence performance, new cost function with weight coefficients is derived by using the tie-line power and frequency deviations of the control areas and their rates of changes according to time. The weight coefficients of this cost function are also tuned with craziness based PSO algorithms. For realistic study, governor dead-band is included to the model. The simulation results show that the dynamic performance of the system is improved by using the proposed controller. The rest of the paper is organized as follows. Section II introduces the control configuration. A governor dead-band is also examined in this section. Overview of PSO and CRAZYPSO is described in Section III. Section IV presents the simulations and its results. Finally, a conclusion is discussed in Section V.

2. Control Configuration

The control system that is used in this paper is composed of a two area interconnected thermal power system. All areas include governor dead-band for system nonlinearity. At the simulation, it is assumed that there is a load demanding in area-1. The linearized model of the controlled system is depicted in Fig.1, and system parameters are also given in Appendix.

In the above model, u_1 and u_2 are the control inputs from the controllers. ΔP_{L1} is step load changes of %1 of the nominal loading in area-1. Δf_1 and Δf_2 are frequency deviations of the control areas and ΔP_{tie} is the changing of the tie-line power.

The governor dead-band is defined as the total magnitude of a sustained speed change within which there is no change in valve position. To represent the governor dead-band in the areas is used describing function approach. The governor dead-band nonlinearity tends to produce a continuous sinusoidal oscillation of natural period of about T_0 = 2 s. This approach is used to linearize the governor dead-band in terms of change and rate of change in the speed [5, 6]. The nonlinearity of the hysteresis is defined as,

$$y = F(x,\dot{x}) \tag{1}$$

there, x is taken as a sinusoidal oscillation with f_0 = 0.5 Hz.

$$x = A \sin w_0 t \tag{2}$$

Since the dead-band nonlinearity tends to give continuously sinusoidal oscillation, such an assumption is quite realistic. Then, the F function can be evaluated as a Fourier series as follows,

$$F(x,\dot{x}) = F_0 + N_1 x + \frac{N_2}{w_0} dx/dt + \ldots \tag{3}$$

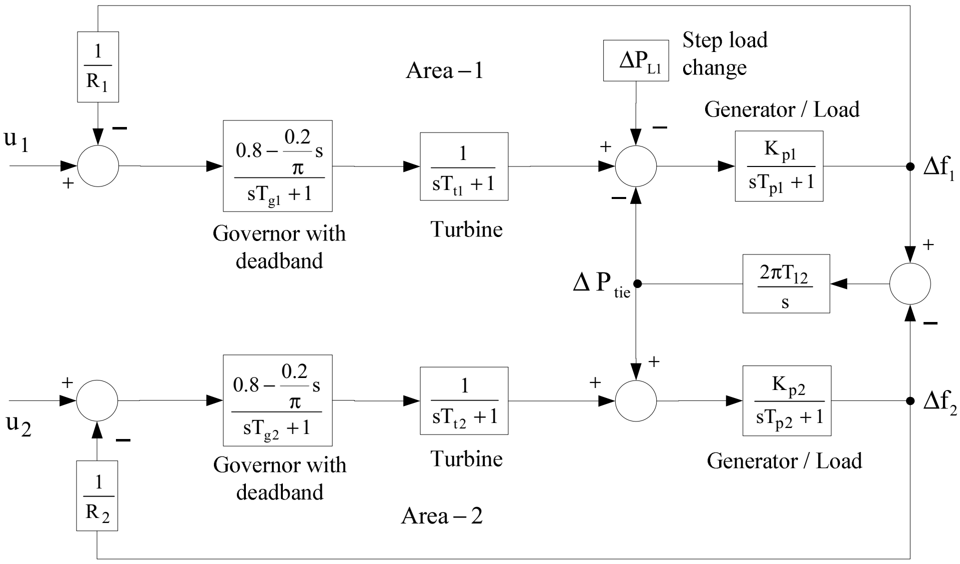

Fig. 1. Block diagram of the two area interconnected thermal power system with governor dead-band

For an approximation, it is enough to consider the first three terms in (3). As the dead-band nonlinearity is symmetrical about the origin, and then F_0 is equal to zero,

$$F(x,\dot{x}) = N_1 x + \frac{N_2}{w_0} dx/dt = DBx \tag{4}$$

where DB denotes the dead-band. In this work, the parameters of the dead-band nonlinearity are determined in literature [5 - 7]. At the result of the analysis, the transfer function of the governor with dead-band nonlinearity can be expressed in (5) [8].

$$G_g = \frac{0.8 - \frac{0.2}{\pi} s}{1 + T_g s} \tag{5}$$

The governor model with dead-band is used as this form in the two area thermal power system model.

3. Craziness Based PSO

Particle swarm optimization is a population-based stochastic optimization algorithm which is first introduced by Kennedy and Eberhart in 1995 [9, 10]. It can be obtained high quality solutions within shorter calculation time and stable convergence characteristics by PSO than other stochastic methods such as genetic algorithm [11].

PSO uses particles which represent potential solutions of the problem. Each particles fly in search space at a certain velocity which can be adjusted in light of proceeding flight experiences. The projected position of ith particle of the swarm x_i, and the velocity of this particle v_i at $(t+1)^{th}$ iteration are defined and updated as the following two equations:

$$v_i^{t+1} = v_i^t + c_1 r_1 \left(p_i^t - x_i^t\right) + c_2 r_2 \left(g_i^t - x_i^t\right) \tag{6}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{7}$$

where, i = 1, ..., n and n is the size of the swarm, c_1 and c_2 are positive constants, r_1 and r_2 are random numbers which are uniformly distributed in [0, 1], t determines the iteration number, p_i represents the best previous position (the position giving the best fitness value) of the i^{th} particle, and g represents the best particle among all the particles in the swarm. The flowchart of standard PSO algorithm is depicted in Fig.2.

At the end of the iterations, the best position of the swarm will be the solution of the problem. It can not always possible to get an optimum result of the problem, but the obtained solution will be an optimal one.

Because of the standard PSO algorithm can fall into premature convergence especially for complex problems with many local optima and optimization parameters, the craziness based PSO algorithm which is particularly effective in finding out the global optimum in very complex search spaces is developed [12]. The main difference between PSO and crazy-PSO is the propagation mechanism to determine new velocity for a particle as follows:

$$v_i^{t+1} = r_2 sign(r_3) v_i^t + (1 - r_3) c_1 r_1 \left(p_i^t - x_i^t\right) + (1 - r_2) c_2 (1 - r_1) \left(g^t - x_i^t\right) \tag{8}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} + P(r_4) sign(r_4) V_{cr} \tag{9}$$

where p_i is the local best position of particle i, and g_i is the global best position of the whole swarm. r_1, r_2, r_3 and r_4 are random parameters distributed uniformly in [0, 1], and c_1, c_2 are named step constants and are taken 2.05 generally. The sign is a function defined as follows for r_3 and r_4,

$$sign(r_3) = \begin{cases} -1 \Leftarrow r_3 \le 0.05 \\ 1 \Leftarrow r_3 > 0.05 \end{cases} \quad (10)$$

$$sign(r_4) = \begin{cases} -1 \Leftarrow r_4 \le 0.5 \\ 1 \Leftarrow r_4 > 0.5 \end{cases} \quad (11)$$

In birds flocking or fish schooling, since a bird or a fish often changes directions suddenly, in the position updating formula, a craziness factor, V_{cr}, is used to describing this behavior. In this study, it is decreased linearly from 10 to 1. $P(r_4)$ is defined as

$$P(r_4) = \begin{cases} 1 \Leftarrow r_4 \le P_{cr} \\ 0 \Leftarrow r_4 > P_{cr} \end{cases} \quad (12)$$

where P_{cr} is a predefined probability of craziness and is introduced to maintain the diversity of the particles. It is taken 0.3 in this study. The crazy-PSO algorithm can prevent the swarm from being trapped in local minimum, which would cause a premature convergence and lead to fail in finding the global optimum [12, 13].

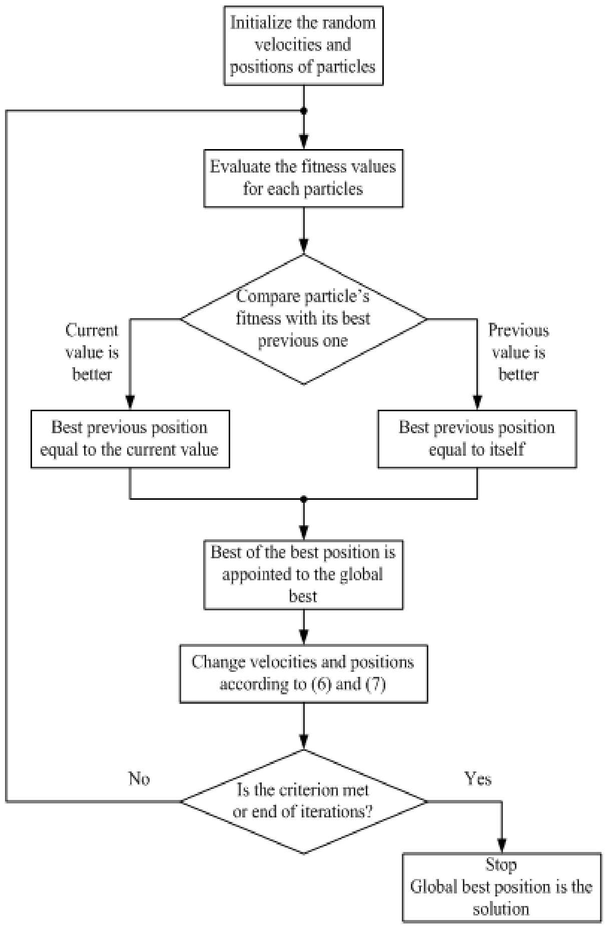

Fig. 2. A flowchart of standard PSO algorithm

4. Simulation Results

The aim of load frequency control is that the steady state errors of the frequency and tie-line power deviations following a step load change are made zero. For this purpose, to obtain the control inputs, PI-controllers are used together with area control errors, ACE_1 and ACE_2.

$$ACE_1 = B_1 \Delta f_1 + \Delta P_{tie1} \quad (13)$$

$$ACE_2 = B_2 \Delta f_2 - \Delta P_{tie2} \quad (14)$$

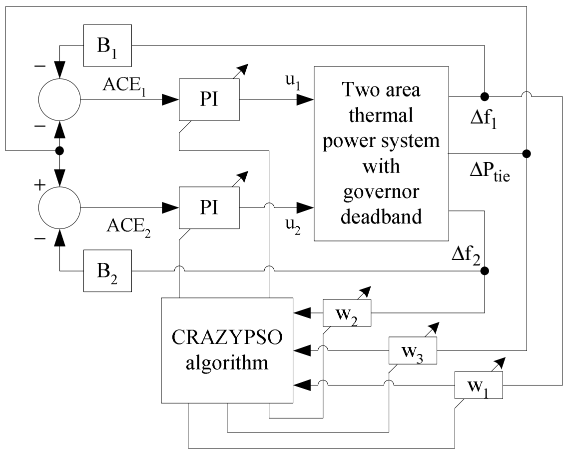

Fig. 3. The load frequency control scheme of two area power system

The control inputs of the power system, u_1 and u_2, are obtained with PI-controllers as below.

$$u_1 = K_{p1} ACE_1 + K_{i1} \int ACE_1 dt \quad (15)$$

$$u_2 = K_{p2} ACE_2 + K_{i2} \int ACE_2 dt \quad (16)$$

The object of obtaining the optimal solutions of control inputs is taken an optimization problem, and the novel cost function in (17) are derived by using the frequency deviations of control areas and tie-line power changes and their rates of changes.

$$J = \int_0^t t \left[\left(w_1 \frac{d\Delta f_1}{dt} \right)^2 + \left(w_2 \frac{d\Delta f_2}{dt} \right)^2 + \left(w_3 \frac{d\Delta P_{tie}}{dt} \right)^2 \right] .dt \quad (17)$$

In this study, the PI-controller gains and the cost function parameters w_1, w_2 and w_3 are tuned with CRAZYPSO algorithm by optimizing the solutions of control inputs. The simulations are realized in case of ΔP_{L1} = 0.01 puMW. The results are obtained by MATLAB 6.5 software run on Core2 of 2 GHz, and RAM of 1 GB. 40 particles are used, and 100 iterations are chosen for converging to solution in the craziness based PSO algorithm.

At the end of the simulations, the tuned parameters of the control system are shown in Table 1, and the settling times of the frequency and tie-line power deviations are represented in Table 2. These results are compared to ones obtained with the integral of time weighted squared error (ITSE) cost function in (18). At these optimizations, CRAZYPSO algorithm is used for tuning the parameters, too.

$$ITSE = \int_0^t t.(ACE_i)^2\,dt \tag{18}$$

It can be seen from these results that the proposed cost function achieve better solution than the standard one. These deviations are also depicted in Fig. 4, Fig. 5, Fig. 6.

Table 1. Tuned parameters obtaining with optimal controller that used ITSE and proposed cost function

	K_p	K_i	w_1	w_2	w_3
Proposed cost function	-0.57	0.19	0.73	0.68	0.78
ITSE	-0.26	0.33	-	-	-

Table 2. Settling times obtaining with optimal controller that used ITSE and proposed cost function

	Δf_1	Δf_2	ΔP_{tie}
Proposed cost function	9.65 s	10.98 s	13.16 s
ITSE	21.66 s	21.67 s	30.80 s

These figures and Table 2 show that the settling time of Δf_1 obtaining with proposed cost function is better than that of Δf_1 obtaining with ITSE of 52.81%, respectively. And then, the settling time of Δf_2 obtaining with proposed cost function is better than that of Δf_2 obtaining with ITSE of 46.36%. In addition to these, the settling time of ΔP_{tie} obtaining with proposed cost function is better than that of ΔP_{tie} obtaining with ITSE of 55.31%. Furthermore, the comparison of settling times according to cost functions is depicted in Fig 7.

5. Conclusions

In this work, to improve the automatic generation control of a two area thermal power system with governor dead-band, the superiority of convergence of CRAZYPSO algorithm in optimizing the parameters of the control system is used. In addition, the new cost function with tuned coefficients is derived by using the frequency and tie-line power deviations and their rates of changes.

At the simulations, both PI-controller gains and weight coefficients of the cost function are optimized with CRAZYPSO algorithm for an optimal controller. The results obtained from the simulations show that the proposed control approach based on self-tuning CRAZYPSO-PI controller with the new cost function achieves better dynamic performances than the standard cost function.

Finally, the obtained results show that CRAZYPSO is an effective algorithm to obtaining the optimal PI-controller for automatic generation control of the power system, and choosing suitable cost function is also quite important for performance of the convergence to the best solution.

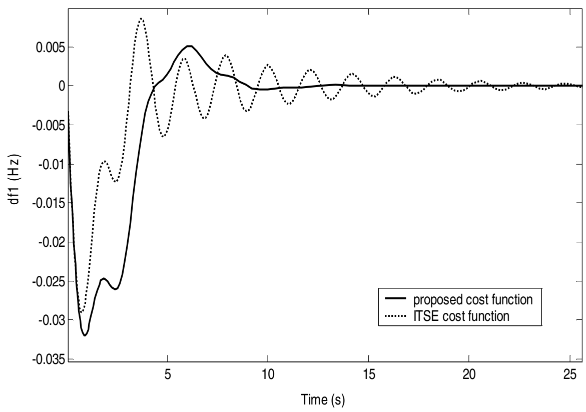

Fig. 4. The deviations of Δf_1 with ITSE and proposed cost function in case of ΔP_{L1}=0.01 puMW

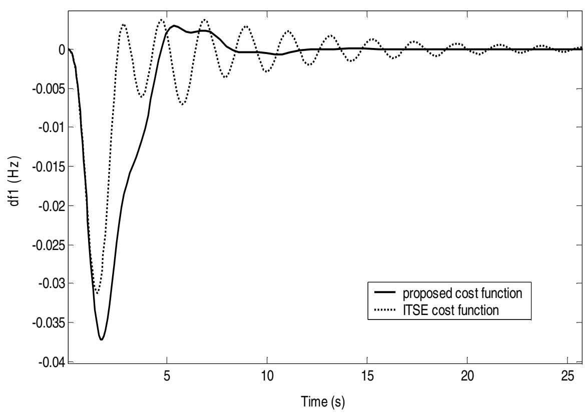

Fig. 5. The deviations of Δf_2 with ITSE and proposed cost function in case of ΔP_{L1}=0.01 puMW

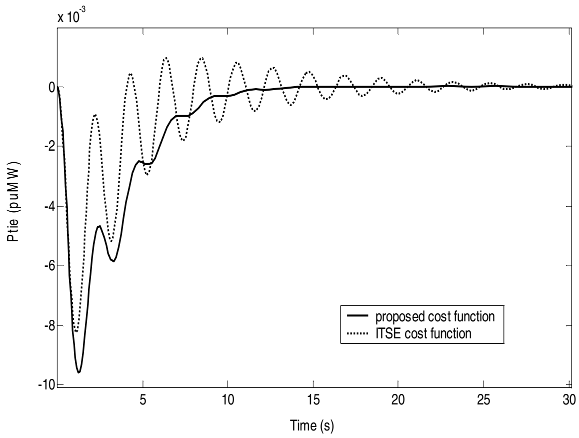

Fig. 6. The deviations of ΔP_{tie} with ITSE and proposed cost function in case of ΔP_{L1}=0.01 puMW

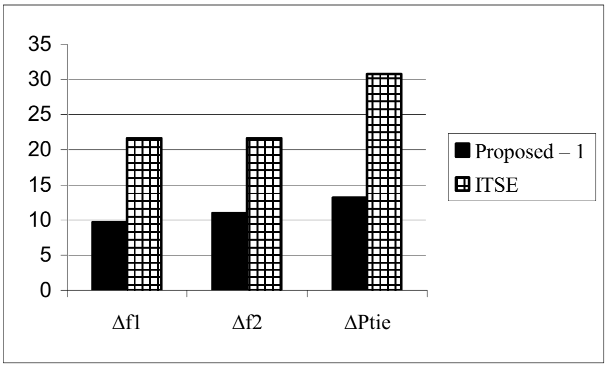

Fig. 7. The comparison of settling times according to cost functions

7. Appendix

$T_{g1,2}$	0.2 s
$T_{t1,2}$	0.3 s
$K_{p1,2}$	120 Hz/puMW
$T_{p1,2}$	20 s
T_{12}	0.0707 MW/rad
$B_{1,2}$	0.425 puMW/Hz
$R_{1,2}$	2.4 Hz/puMW

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