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Optimal Decentralized Load Frequency Control Using HPSO Algorithms in Deregulated Power Systems

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Abstract: Load Frequency Control (LFC) is one the most important issues in electrical power system design/operation and is becoming much more significant recently with increasing size, changing structure and complexity in interconnected power systems. In practice LFC systems use simple Proportional-Integral (PI) or Integral (I) controllers. However, since the PI or I control parameters are usually tuned based on classical or trial-and-error approaches, they are incapable of obtaining good dynamic performance for various load changes scenarios in multi-area power system. For this reason, in this study the PI and I control parameters are tuned based on Hybrid Particle Swarm Optimization (HPSO) algorithm method for LFC control in two-area power system. Because HPSO is an optimization method, therefore, in the uncertainty area of controller parameters, finds the best parameters for controller and obtained controller is an optimal controller. A two-area power system example is given to illustrate proposed methods. To show effectiveness of proposed method and compare the performance of optimized PI and I type controllers, several time-domain simulation for various load changes scenarios are presented. Simulation results emphasis on the better performance of optimized PI controller in compared to optimized I controller in LFC.

Key words: Load Frequency Control (LFC), Hybrid Particle Swarm Optimization (HPSO), decentralized control, deregulated power systems

INTRODUCTION

Large-scale power systems are normally composed of interconnected subsystems or control areas. The connection between the control areas is done using tie lines. Each area has its own generator or group of generators and it is responsible for its own load and scheduled interchanges with neighboring areas. Because loading of a given power system is never constant and to ensure the quality of power supply, a load frequency controller is needed to maintain the system frequency at the desired nominal value. It is known that changes in real power affect mainly the system frequency and the input mechanical power to generators is used to control the frequency of the output electrical power. In a deregulated power system, each control area contains different kinds of uncertainties and various disturbances due to increased complexity, system modeling errors and changing power system structure. A well designed and operated power system should cope with changes in the load and with system disturbances and it should provide acceptable high level of power quality while maintaining both voltage and frequency within tolerable limits[1-6].

During the last three decade, various control strategies for LFC have been proposed[1-18]. This extensive research is due to fact that LFC constitutes an important function on power system operation where the main objective is to regulate the output power of each generator at prescribed levels while keeping the frequency fluctuations within pre-defined limits. Robust adaptive control schemes have been developed[4-7] to deal with changes in system parametric under LFC strategies. A different algorithm has been presented[8] to improve the performance of multi-area power systems. Viewing a multi-area power system under LFC as a decentralized control design for a multi-input multi-output system, it has been shown[9] that a group of local controllers with tuning parameters can guarantee the overall system stability and performance. The result reported in[4-9] demonstrates clearly the importance of robustness and stability issues in LFC design. In addition, several practical points have been addressed in[10-15] which include recent technology used by vertically integrated utilities, augmentation of filtered area control error with LFC schemes and hybrid LFC that encompasses an independent system operator and bilateral LFC.

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The applications of artificial neural networks, genetic algorithms, fuzzy logic and optimal control to LFC have been reported in[16-18]. The objective of this study is to investigate the load frequency control and inter area tie-power control problem for a multi-area power system taking into consideration the uncertainties in the parameters of system.

PI type and I type controllers are considered to LFC control. An optimal control scheme based hybrid particle swarm optimization (HPSO) Algorithm method is used for tuning the parameters of these PI and I controllers. The proposed controller is simulated for a two-area power system.

To show effectiveness of proposed method and also compare the performance of these two controllers, several changes in demand of first area, demand of second area and demand of two areas simultaneously are applied. Simulation results indicate that HPSO controllers guarantee the good performance under various load conditions.

MATERIALS AND METHODS

A two-control area power system, shown in Fig. 1 is considered as a test system[14]. The state-space model of foregoing system is as (1)[14].

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx \end{cases} \qquad (1)$$

Where:

$$u = [\Delta P_{D1}, \Delta P_{D2}, u_1, u_2]$$
$$y = [y_1, y_2] = [\Delta f_1, \Delta f_2, \Delta P_{tie}]$$
$$x = [\Delta P_{G1} \quad \Delta P_{T1} \quad \Delta f_1 \quad \Delta P_{tie} \quad \Delta P_{G2} \quad \Delta P_{T2} \quad \Delta f_2]$$

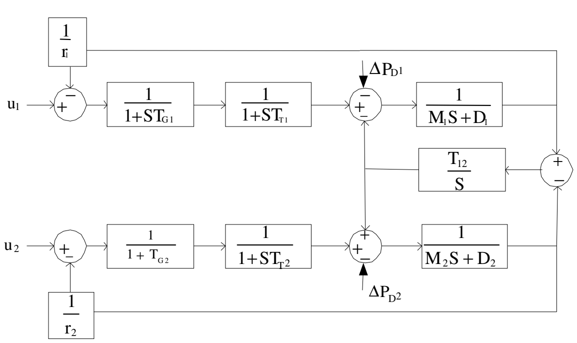

Fig. 1: Block diagram of two-area power system without LFC

$$B = \begin{bmatrix} 0 & 0 & \frac{1}{M_1} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{M_2} \\ \frac{1}{T_{G1}} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{T_{G2}} & 0 & 0 \end{bmatrix}$$

$$A = \begin{bmatrix} \frac{-1}{T_{G1}} & 0 & \frac{-1}{r_1 T_{G1}} & 0 & 0 & 0 & 0 \\ \frac{1}{T_{T1}} & \frac{-1}{T_{T1}} & 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{M_1} & \frac{-D_1}{M_1} & \frac{-1}{M_1} & 0 & 0 & 0 \\ 0 & 0 & T_{12} & 0 & 0 & 0 & -T_{12} \\ 0 & 0 & 0 & 0 & \frac{-1}{T_{G2}} & 0 & \frac{-1}{r_2 T_{G2}} \\ 0 & 0 & 0 & 0 & \frac{1}{T_{T2}} & \frac{-1}{T_{T2}} & \\ 0 & 0 & 0 & \frac{1}{M_2} & 0 & \frac{1}{M_2} & \frac{-D_2}{M_2} \end{bmatrix}$$

The parameters of model, defined as follow:

Δ	=	Deviation from nominal value
$M = 2H$	=	Inertia constant
D	=	Damping constant
R	=	Gain of speed droop feedback loop
T_t	=	Turbine time constant
T_G	=	Governor time constant

The typical values of system parameters for nominal operation condition are given in appendix[12].

This study focuses on optimal tuning of controllers for LFC and tie-power control using HPSO algorithm. The aim of the optimization is to search for the optimum controller parameter setting that maximize the minimum damping ratio of the system. On the other hand in this study the goals are control of frequency and inter area tie-power with good oscillation damping and also obtaining a good performance under all operating conditions and various loads and finally designing a low-order controller for easy implementation.

PSO AND HPSO ALGORITHMS

A novel population based optimization approach, called particle swarm optimization (PSO), was introduced first in[19]. In a PSO system, multiple candidate solutions coexist and collaborate simultaneously. Each solution candidate, called a "particle", flies in the problem space (similar to the search process for food of a bird swarm) looking for the optimal position. A particle with time adjusts its position to its own experience, while adjusting to the experience of neighboring particles. If a particle discovers a promising new solution, all the other particles will move closer to it, exploring the region more thoroughly in the process.

This new approach features many advantages; it is simple, fast and can be coded in few lines. Also its strong requirement is minimal. Moreover, this approach is advantageous over evolutionary and genetic algorithm in many ways. First, PSO has memory. That is, every particle remembers its best solution (global best). Another advantage of PSO is that the initial population of the PSO is maintained and so there is no need for applying operators to the population, a process that is time-and memory-storage-consuming. In addition, PSO is based on constructive cooperation between particles, in contrast with the genetic algorithms, which are based on the survival of the fittest[19-22].

Steps of PSO: Steps of PSO as implemented for optimization are[19-29]:

Step 1: Initialize an array of particles with random positions and their associated velocities to satisfy the inequality constraints.
Step 2: Check for the satisfaction of the equality constraints and modify the solution if required.
Step 3: Evaluate the fitness function of each particle.
Step 4: Compare the current value of the fitness function with the particles previous best value (pbest). If the current fitness value is less, then assign the current fitness value to pbest and assign the current coordinates (positions) to pbestx.
Step 5: Determine the current global minimum fitness value among the current positions.
Step 6: Compare the current global minimum with the previous global minimum (gbest). If the current global minimum is better than gbest, then assign the current global minimum to gbest and assign the current coordinates (positions) to gbestx.
Step 7: Change the velocities.
Step 8: Move each particle to the new position and return to step 2.
Step 9: Repeat step 2-8 until a stop criterion is satisfied or the maximum number of iterations is reached.

PSO and HPSO algorithm definition: The PSO definition is presented as follows[19,22,26]:

- Each individual particle i has the following properties:
  x_i = A current position in search space.
  v_i = A current velocity in search space.
  y_i = A personal best position in search space.
- The personal best position p_i corresponds to the position in search space, where particle i presents the smallest error as determined by the objective function f, assuming a minimization task.
- The global best position denoted by g represents the position yielding the lowest error among all the p_i's.

Equation 2 and 3 define how the personal and global best values are updated at time k, respectively. In below, it is assumed that the swarm consists of s particles. Thus, $i \in \mathbf{1},\ldots,s$

$$p_i^{k+\mathbf{1}} = \begin{cases} p_i^k & \text{if } f(p_i^k) \le f(X_i^{k+\mathbf{1}}) \\ X_i^{k+\mathbf{1}} & \text{if } f(p_i^k) > f(X_i^{k+\mathbf{1}}) \end{cases} \tag{2}$$

$$\begin{aligned} g^k \in \left\{p_\mathbf{1}^k, p_\mathbf{2}^k, \ldots, p_s^k\right\} \;&|\; f(g^k) \\ = \min \;&\left\{f(p_\mathbf{1}^k), f(p_\mathbf{2}^k) \ldots f(p_s^k)\right\} \end{aligned} \tag{3}$$

During each iteration, every particle in the swarm is updated using 4 and 5. Two pseudorandom sequences $r_1 \sim U(0,1)$ and $r_2 \sim U(0,1)$ are used to affect the stochastic nature of the algorithm.

$$\begin{aligned} v_i^{k+1} = w \times v_i^k + c_1 \times \text{rand}()_1 \times (p_i^k - X_i^k) \\ + c_2 \times \text{rand}()_2 \times (g^k - X_i^k) \end{aligned} \tag{4}$$

$$X_i^{k+1} = X_i^k + v_i^{k+1} \tag{5}$$

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \tag{6}$$

$$v_{max} = k \times x_{max} \qquad 0.1 \le k \le 1 \tag{7}$$

Where:
v_i^k = Velocity of i^{th} particle at k^{th} iteration.
v_i^{k+1} = Velocity of i^{th} particle at $(k+1)^{th}$ iteration.

w = Inertia weight,
X_i^k = Position of i^{th} particle at k^{th} iteration.
X_i^{k+1} = Position of i^{th} particle at $(k+1)^{th}$ iteration.
c_1, c_2 = Positive constants both equal to 2.
iter, $iter_{max}$ = Iteration number and maximum iteration number.
$rand()_1$, $rand()_2$ = Random number selected between 0 and 1.

Evolutionary operators such as selection, crossover and mutation have been applied into the PSO. By applying selection operation in PSO, the particles with the best performance are copied into the next generation, therefore, PSO can always keep the best performed particles. By applying crossover operation, information can be exchanged or swapped between two particles so that they can fly to the new search area as in evolutionary programming and genetic algorithms. Among the three evolutionary operators, the mutation operators are the most commonly applied evolutionary operators in PSO. The purpose of applying mutation to PSO is to increase the diversity of the population and the ability to have the PSO to escape the local minima[19-28] . HPSO uses the mechanism of PSO and a natural selection mechanism utilizing genetic algorithm.

CONTROLLER DESIGN USING HPSO ALGORITHM

In this study P-I and I type controllers optimized by HPSO are designed for LFC and tie-power control. The goals are control of frequency and inter area tie-power with good oscillation damping, also obtaining a good performance. The structure of system with PI controller is shown in Fig. 2[26,29]. The area control error (ACE) for the i^{th} area is defined as:

$$\Delta CE_i = \Delta P_{tiei} + \Delta f_i \tag{8}$$

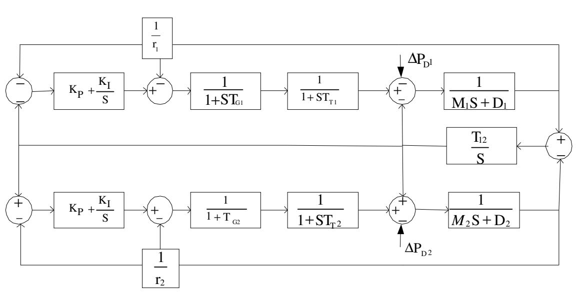

Fig. 2: Block diagram of a two-area power system with controllers

with PI controller, the conventional automatic generation controller has a control equation of the form 9.

$$\Delta PC_i = K_{Pi}\left(\Delta P_{tiei} + \Delta f_i\right) + K_{Ii}\int\left(\Delta P_{tiei} + \Delta f_i\right) \tag{9}$$

With I controller; the conventional automatic generation controller has a linear integral control strategy as 10.

$$\Delta PC_i = K_{Ii}\int\left(\Delta P_{tiei} + \Delta f_i\right) \tag{10}$$

Where K_{Pi} is the gain of the proportional controller and K_{Ii} is the gain of the integral controller for the i^{th} area.

In this study, the optimum values of the parameters K_P and K_I for PI controller and K_I for I controller, who minimize an array of different performance indices, are easily and accurately computed using a HPSO. In a typical run of the HPSO, an initial population is randomly generated. This initial population is referred to as the 0^{th} generation. Each individual in the initial population has an associated performance index value. Using the performance index information, the HPSO then produces a new population.

In order to obtain the value of the performance index for each of the individuals in the current population, the system must be simulated. The HPSO then produces the nest generation of individuals using the reproduction crossover and mutation operators.

These processes are repeated until the population is converged and optimum value of parameters found. To simplify the analysis, the two interconnected areas were considered identical. The optimal parameter values are such that:

$$K_{P1} = K_{P2} = K_P \quad \text{and} \quad K_{I1} = K_{I2} = K_I$$

The nominal system parameters are given in appendix. The performance index considered in this study is of the form:

$$Per.\_Ind. = \int_0^\infty t\left(\alpha|\Delta f_1| + \beta|\Delta f_2| + \gamma|\Delta P_{tie}|\right)dt \tag{11}$$

To compute the optimum parameter values, a unit step load change is assumed in area 1 and the performance index is minimized using a HPSO algorithm. In the next section, the optimum values of the parameters K_P and K_I for PI controller and K_I for I controller, resulting from minimizing the performance index are presented. In this case performance index was considered with:

$$\alpha = 1, \beta = 1, \gamma = 1$$

(frequency deviations in both areas and tie-power deviation are equally penalized).

It should be noted that the α, β and γ are weighting coefficients chosen by the designer. The optimum value of the parameters K_P and K_I for performance index as obtained using HPSO algorithm is summarized in the Table 1. The optimum value of the parameter K_I for performance index as obtained using HPSO algorithm is summarized in the Table 2.

Table 1 and 2 give the optimum values for K_P, K_I and the corresponding values of the performance index for the two cases considered.

RESULTS AND DISCUSSION

In this section different comparative cases are examined to show the effectiveness of proposed HPSO method for optimizing controller parameters (PI and I type). These cases have been evaluated extensively by time-domain simulation, using commercially available software package[30].

It is clear that considering PI type controller results in a decrease of the optimum value of the performance index. This in turn will lead to an increase damping in the dynamic response of the system and clearly show that PI controller has a better performance in compare to I controller in LFC control. In continue, the simulation result clearly shows this subject.

Step increase in demand of the first area (ΔP_{D1}): As the first test case, a step increase in demand of the first area (ΔP_{D1}) is applied at operating point 1 (nominal operating point). The frequency deviation of the first area $\Delta\omega_1$ and the frequency deviation of the second area $\Delta\omega_2$ and inter area tie-power signals of the closed-loop system are shown in Fig. 3 and 5. Using PI controller, the frequency deviations and inter area tie-power are quickly driven back to zero and PI controller has the best performance in control and damping of frequency and tie-power in compare to I controller. Also responses without any controller cannot be driven back to zero and will have a steady-state error.

Step increase in demand of the second area (ΔP_{D2}): In this case, a step increase in demand of the second area (ΔP_{D1}) is applied at operating point 2. The

Table 1: Optimum values of K_P and K_I for PI controller

K_P	2.2264
K_I	6.6567
Performance index	0.6146

Table 2: Optimum value of K_I for I controller

K_I	0.6812
Performance index	3.7226

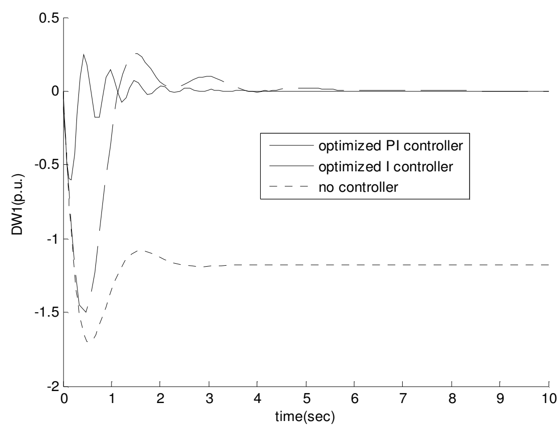

Fig. 3: Dynamic response of $\Delta\omega_1$ following a step change in demand of the first area (ΔP_{D1})

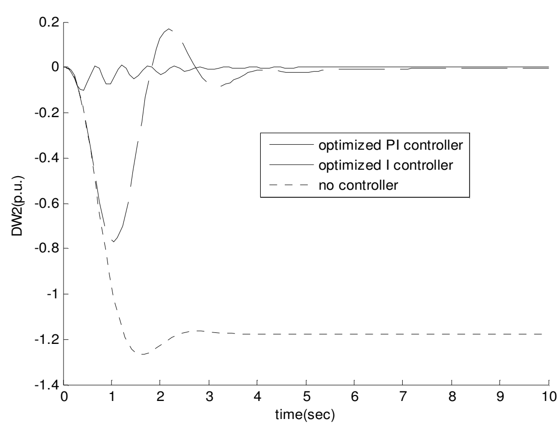

Fig. 4: Dynamic response of $\Delta\omega_2$ following a step change in demand of the first area (ΔP_{D1})

frequency deviation of the first area $\Delta\omega_1$ and the frequency deviation of the second area $\Delta\omega_2$ and inter area tie-power signals of the closed-loop system are shown in Fig. 6-8. Using PI controller, the frequency deviations and inter area tie-power quickly driven back to zero and PI controller has the best performance in control and damping of frequency and tie-power in

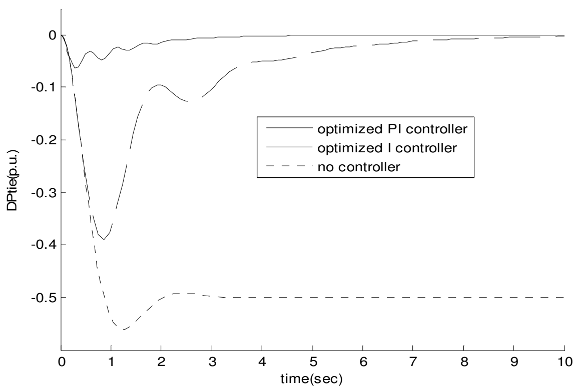

Fig. 5: Dynamic response of ΔP_{tie} following a step change in demand of the first area (ΔP_{D1})

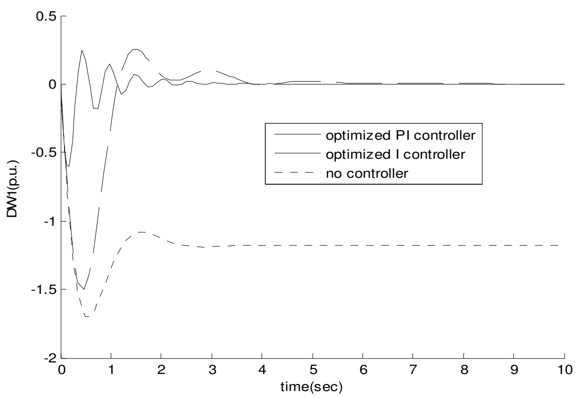

Fig. 6: Dynamic response of $\Delta\omega_1$ following a step change in demand of the second area (ΔP_{D2})

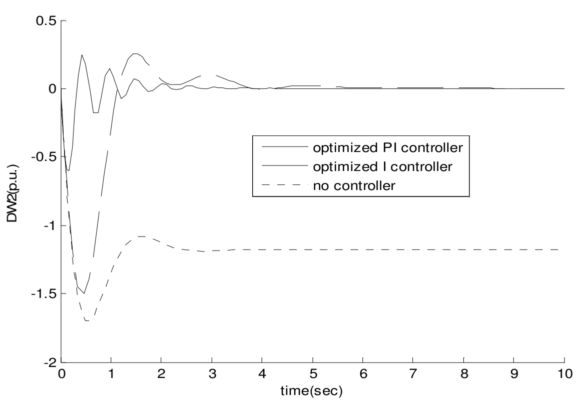

Fig. 7: Dynamic response of $\Delta\omega_2$ following a step change in demand of the second area (ΔP_{D2})

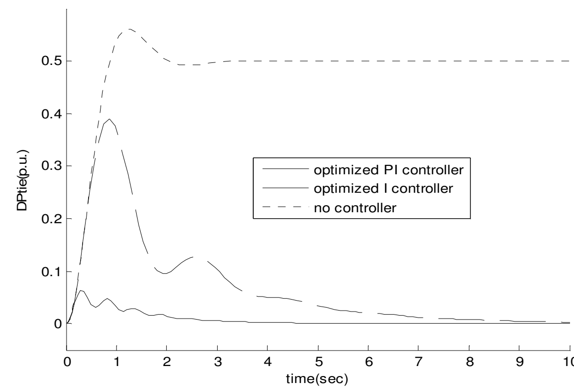

Fig. 8: Dynamic response of ΔP_{tie} following a step change in demand of the second area (ΔP_{D2})

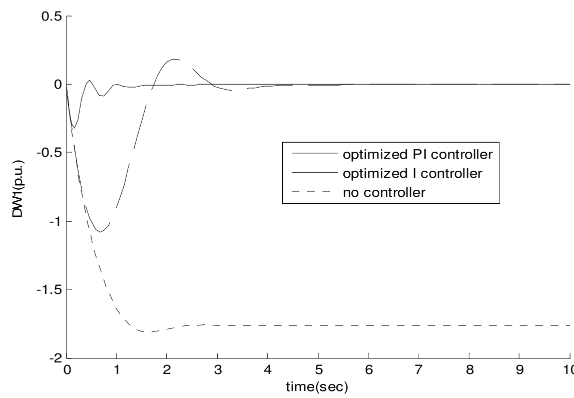

Fig. 9: Dynamic response of $\Delta\omega_1$ following a step change in demand of two areas simultaneously

compare to I controller. Also responses without any controller cannot be driven back to zero and will have a steady state error.

Step increase in demand of the first and second area simultaneously: In this case, a 0.5 step increase in demand of the first area (ΔP_{D1}) and step increases in demand of the second area (ΔP_{D2}) simultaneously are applied at operating point 3. The signals of the closed-loop system are shown in Fig. 9-11. Using optimized PI controller, the frequency deviations and inter area tie-power quickly driven back to zero and PI controller has the best performance in compare to optimized I controller. Also responses without any controller cannot be driven back to zero and will have a steady-state error.

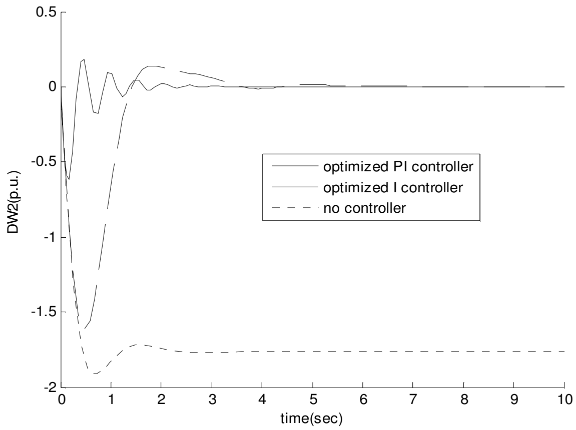

Fig. 10: Dynamic response of $\Delta\omega_2$ following a step change in demand of two areas simultaneously

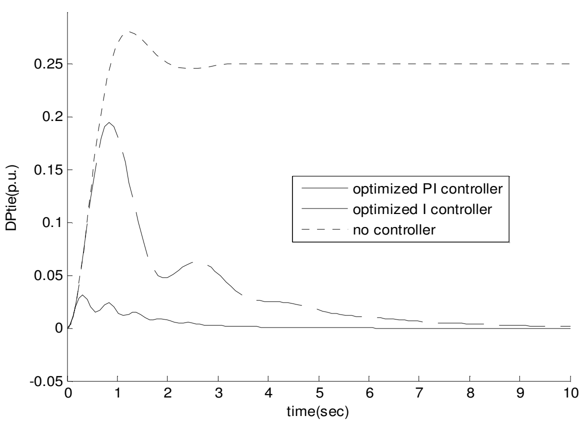

Fig. 11: Dynamic response of ΔP_{tie} following a step change in demand of two areas simultaneously

CONCLUSION

In this study HPSO has been successfully applied to tune the parameters of conventional automatic generation systems of the P-I type and I type controller. A two-area power system is assumed to demonstrate the proposed method. The performance index has been considered as the integral of time-multiplied absolute value of the error. For performance index, a digital simulation of the system is carried out and optimization of the parameters of the automatic generation control (AGC) systems is achieved in a simple and elegant manner through the effective application of HPSO algorithm. These results and the suitability of HPSO to nonlinear problems, open the door to study the effect of the generation rate constraints on the optimal value of the AGC parameters.

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