Particle Swarm Intelligence Based Optimization Controller Applied to Two Area Interconnected Power Systems

V. Jeyalakshmi and P. Subburaj

Abstract This paper presents the optimal performance of Load Frequency control (LFC) in interconnected two-area power systems. Proportional–Integral (PI) controllers are commonly used for LFC systems in power industry. But the dynamic behaviors in the presence of variations in load changes with different operating conditions are needed to be improved. This paper proposes Particle Swarm Optimization (PSO) based Load Frequency Control for improving the dynamic performance of the system. A two area interconnected power system, having different generating units is considered to be equipped with Proportional Integral and Derivative (PID) controller. PSO algorithm is implemented to search the optimal controller parameters by minimizing the time domain objective function. The performance of the proposed PID controller has been evaluated by the performance of the conventional controller and the controller tuned by Genetic algorithm (GA) in order to demonstrate the superior efficiency of the proposed PSO algorithm. Simulation results proved that the proposed algorithm is moderately fast algorithm and yields true optimal gains with minimum overshoot, minimum undershoot, minimum rise time and minimum settling time for any power system. Furthermore, the dynamic behavior of the proposed controller under variations of system parameters and load changes are better than that of conventional and GA controllers.

Keywords Load frequency control · Genetic algorithm · Optimization technique · Power system · Particle swarm optimization

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1 Introduction

It is well known that three-phase alternating current (AC) is generally used to transmit the electricity. During the transmission, both the active power balance and the reactive power balance must be maintained between the generation and utilization of the AC power. The power balances correspond to two equilibrium points: frequency and voltage. A good quality of the electric power system requires both the frequency and the voltage to be remain at constant values during operation. It will be impossible to maintain the balances of both the active and reactive powers without proper compensation. As a result of the imbalance, the frequency and the voltage levels will be varied with the change of variations in the loads. Thus a control system is essential to cancel the effects of the random load changes and to keep the frequency and the voltage at the constant values [1]. The active power and frequency control is referred to as load frequency control (LFC). The foremost task of LFC is to keep the frequency constant against the randomly varying active power loads, which are also referred to as unknown external disturbance. Another task of the LFC is to regulate the tie-line power exchange error [2]. A typical large-scale power system is composed of several areas of generating units interconnected together and power is exchanged between utilities. A major problem in the parallel operation of interconnected power systems is the control of frequency and inter-area tie-line power flow control. The objective of the LFC in interconnected power systems is to maintain the frequency of each area and to keep tie-line power flows within some pre-specified tolerances by adjusting the outputs of the high capacity generators when fluctuations occur in the load demands [3]. There have been increasing interest in designing load frequency controllers with better performance during the past years and many control strategies have been developed for LFC. The first proposed control strategy was a proportional integrator (PI) controller, which is nowadays widely used in the industry [4]. The main drawback of this controller is that the dynamic performance of the system is limited by its integral gain.

Despite the potential of the modern control techniques with different structure, Proportional Integral Derivative (PID) type controller is still widely used for solution of the LFC problem [4]. This is because due to it's performed well for a wider class of process. Also, it gives robust performance for a wide range of various operating conditions and easy to implement. The PID controller parameters tuning are usually done by trial and error methods based on the conventional experiences. Hence, they are not capable of providing good robust performance for power system subjected to different kinds of uncertainties and disturbances. An appropriate selection of PID controller parameters results in satisfactory performance during system upsets. Thus, the optimal tuning of a PID gain is required to get the desired level of robust performance [5, 6]. Since the optimal setting of PID controller gains is a “multimodal” optimization problem (i.e., there exists more than one local optimum) and more complex due to nonlinearity, complexity and time-variability of the real world power systems operation. Hence, the local optimization techniques, which are well elaborated upon, are not suitable for such a problem. Many studies have been carried out in the past on this important issue in power systems such as linear feedback, optimal control and variable structure control [7–9] have been proposed in order to improve the robust performance. These controllers may be improper in some operating conditions. This could be due to the complexity of the power systems such as nonlinear load characteristics with variable operating points. The availability of an accurate model of the system under study plays a crucial role in the development of the most control strategies like optimal control. However, an industrial process, such as a power system, contains different kinds of uncertainties due to changes in the system parameters and its characteristics, loads variations and errors in the modeling.

Recently, a global optimization technique like Genetic Algorithm has attracted the attention in the field of controller parameter optimization [10–12]. Unlike other techniques, GA is a population based search algorithm, which works with a population of strings that represent different solutions. Therefore, GA has implicit parallelism that enhances its search capability and the optima can be located swiftly when applied to the complex optimization problems. Unfortunately recent research has found some drawbacks in GA performance [13] such as the parameters being optimized are highly correlated. They need to run several times to obtain the best optimal solution [14, 15]. Also, the premature convergence of GA degrades its performance and reduces its search capability resulting in sub-optimal solutions with revisiting the same solutions. To overcome this problem of sub-optimal convergence, powerful computational intelligent evolutionary techniques as Particle Swarm Optimization is proposed by the authors [16–18] to optimize the PID gains of the controller for the Automatic Generation Control problem in power systems. PSO is a computational intelligence-based technique that is not largely affected by the size and the nonlinearity of the problem, and can converge to the optimal solution in many problems where most analytical methods fail to converge. PSO has been applied to various fields of power system including economic dispatch problems as well as in optimization problems in electric power systems [19]. It can therefore be effectively applied to different optimization problems in power systems.

In this work, different controllers such that, Conventional PID, Genetic Algorithm based PID (GAPID) and Particle Swarm Optimization based PID (PSOPID) are developed. The comparative study has been made between these controllers by varying the system parameters with different load conditions. In this simulation study, two area power systems with two different parameters are chosen and load frequency control of this system is made based on optimal tuning of PID controller parameters. Simulation results show that the overshoots, undershoots and settling times with the proposed PID controller are better than the outputs of the conventional and GA controllers under a wide range of changing load conditions with different system parameter changes occurred.

2 Dynamic Model of the System

A two-area interconnected power systems with different units are considered here. Figure 1 shows the representation of the two-area interconnected power systems. The two areas may have the combinations of different units. (Thermal—Hydro units). The detailed transfer function models of speed governors, thermal non-reheat turbines and hydro turbines are developed. Governors are the units that are used in power systems to sense the frequency bias caused by the load change and it can be cancelled by varying the inputs of the turbines. The transfer function of governor unit is given by [20]:

$$G_g(S) = \frac{\Delta P_e(s)}{\Delta P_v(s)} = \frac{1}{T_{g1}s + 1}$$

where ΔPe—change in electrical power; ΔP_v—Change in gate/valve position; T_{g1}—Governor time constant.

A turbine unit in power systems is used to transform the natural energy, such as the energy from steam or water, into mechanical power that is supplied to the input of the generator. In LFC model, there are three kinds of commonly used turbines: non-reheat, reheat and hydraulic turbines, all of which can be modeled by transfer functions. The transfer function of the non-reheat turbine is represented as follows:

$$G_{NR}(S) = \frac{\Delta P_m(s)}{\Delta P_v(s)} = \frac{1}{T_{t1}s + 1}$$

where ΔPm—change in mechanical power; T_{t1}—Time delay.

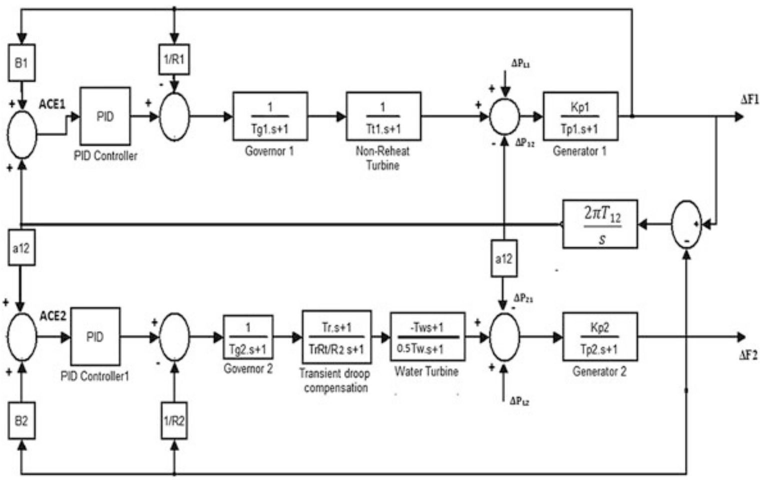


Fig. 1 Two area interconnected power system for test case B1

A generator unit in power systems converts the mechanical power (ΔPm) received from the turbine into electrical power (Δf). The transfer function of the generator is represented as follows:

$$G(S) = \frac{\Delta f(s)}{\Delta P_m(s)} = \frac{K_{pi}}{T_{pi}s + 1}$$

where K_{pi}—System gain for area i; T_{pi}—Generator time constant for area i.

Hydraulic turbines are non-minimum phase units due to the water inertia. In the hydraulic turbine, the water pressure response is opposite to the gate position change at first and recovers after the transient response. Thus the transfer function of the hydraulic turbine is in the form of,

$$\mathrm{G_H(S)} = \frac{\Delta \mathrm{P_m(s)}}{\Delta \mathrm{P_v(s)}} = \left(\frac{-\mathrm{T_w s}}{0.5\mathrm{T_w s} + 1}\right)$$

where T_w—water starting time.

For stability concern, a transient droop compensation part in the governor is needed for the hydraulic turbine. The transfer function of the transient droop compensation part is given by

$$\mathrm{G_{TD}(S)} = \left(\frac{\mathrm{T_r s} + 1}{\mathrm{T_r}\left(\frac{\mathrm{R_t}}{\mathrm{R_2}}\right)\mathrm{s} + 1}\right)$$

where T_r—reset time; R_t and R_2—temporary droop and permanent droop respectively.

2.1 Problem Description

The LFC problem considered here is the perturbations in small load and system parameter changes which continuously disturb the normal operation of a power system. To overcome the above difficulty we propose an optimal controller to provide better performance when disturbances are occurring. In practical cases we are having different units are interconnected together to meet the increasing demand. Interconnection established increases the overall system reliability. Even if some generating units in one area fail, the generating units in the other area can compensate to meet the load demand [21]. In this work, the frequency and tie line power deviation among different units are observed and the dynamic performance of the system is also analyzed. Since the two areas are interconnected by tie-lines, a single PID controller whose input contains the error signal and their changes in both areas are used. The PID controller has the following structure [22]:

$$\mathrm{K}(s) = K_p + \frac{K_i}{s} + K_d s \tag{1}$$

where K_p is the proportional gain, K_i is the integral gain and K_d is the derivative gain. The control signal for PID controller can be given in the following equation.

$$U_i(s) = -K(s) * ACE_i(s) \tag{2}$$

The control action which depends upon the Area Control Error (ACE) which is a linear combination of net tie-line power error (ΔP_{tie}) and frequency error (Δf) and represented as [14]:

$$ACE_i = \Delta P_{tie,i} + b_i \Delta f_i \tag{3}$$

where b_i is frequency bias coefficient, $\Delta P_{tie,i}$ is the tie-line interchange error and Δf_i is the frequency error component. This signal is used to regulate the generator output power based on network load demand. The objective is to obtain the better transient response under varying system parameters with various load conditions. The transient response can be optimized that means minimum undershoot, minimum overshoot and minimum settling time of DF1, DF2 and Delta P_{tie} for area 1 and area 2 respectively. This is achieved through optimization of PID Gains of the PID controllers by any of the optimization techniques. A performance index can be defined by the Integral of Time multiply Absolute Error (ITAE) of the frequency deviation of both areas and tie line power. The objective function J is set to be

$$J(K_P, K_i, K_d) = \int_0^t t(|\Delta f_1| + |\Delta f_2| + |\Delta P_{tie}|)dt \tag{4}$$

It is clear that the controller with lower ITAE is better than the other controllers. To compute the optimum parameter values, 10 and 25 % step change in ΔP_{L1} and ΔP_{L2} is assumed and the performance index is minimized using optimization algorithms.

3 Optimization Techniques

Proper selection of PID controller parameters is necessary for the satisfactory operation of the system. In this work, the problem of PID controller parameter selection is formulated as an optimization problem, the objective function of which is given by Eq. (4). Optimization techniques such as GA and PSO are applied to the above optimization problem to search for the optimum value of the controller parameters. The implementations of these algorithms are given in the following sections.

3.1 Genetic Algorithm

Genetic algorithm (GA) is one of the optimization methods based on the mechanics of natural selection and genetics. An implementation of genetic algorithm begins with a population of chromosomes [23]. The major steps involved are the generation of population of solutions, finding the objective function and fitness function and the application of genetic operators. There are four operators such as, selection, reproduction, crossover and mutation. In nature, the individual can have better survival traits that will survive for a longer period of time. This in turn provides it a better chance to produce offspring with its genetic material. Therefore, after a long period of time, the entire population will consist of lots of genes from the superior individuals and less from the inferior individuals. In a sense, the fittest survived and the unfit died out. This force of nature is called natural selection. Changes occur during reproduction. The chromosomes from the parents exchange randomly by a process called crossover. Therefore, the offspring exhibit some traits of the father and some traits of the mother. A rare process called mutation also changes some traits.

An important characteristic of genetic algorithm is the coding of variables that describes the problem. The most common coding method is to transform the variables into a binary string or vector; GA performs best when the solution vectors are binary. Just like natural genetics a chromosome (a string) will contain some genes (binary bits). A population size is chosen which consists of several parent strings. The strings are then subjected to an evaluation of fitness function and its least fitness value will be selected for the next generation. The selected strings will produce new off springs by reproduction, cross over and mutation operation. Hence a new population which is different from old population is produced in each cycle of iteration. The whole process is repeated for several iterations till or near optimal solution is reached.

While applying GA to obtain optimal PID controller parameters, the following factors are needed to be considered.

1. Representation of Decision variables
2. Formation of Fitness function

Variable Representation
Each individual in the genetic population represents a candidate solution. In the binary-coded GA, the solution variables are represented by a string of binary alphabets. For tuning of PID controller, the elements of the solution consist of Proportional gain (Kp), Integral gain (Ki) and Derivative gain (K_d). These variables are represented as binary strings in the GA population. With binary representation, an individual in the GA population for computing optimal controller parameters will look like the following:

$$\underbrace{1011100111}_{K_p}\quad\underbrace{101101101}_{K_i}\quad\underbrace{1011100101}_{K_d}$$

Evaluation of the individuals in the population is accomplished by calculating the objective function of the problem using the parameter set. The result of the objective function is used to calculate the fitness value of the individual. Fitter chromosomes have higher probabilities of being selected for the next generation. The fitness function is a reciprocal of the performance criterion as in (4). Hence, the minimization of objective function given by (4) is transformed to a fitness function to be maximized as follows:

$$F_{fitness} = \frac{1}{1 + F_{cost}} \tag{5}$$

For designing the controller, cost function (F_{cost}) can be assumed as minimization of "Integral time Absolute Error" (ITAE), as shown in Eq. (4).

In this research work, the PID Controller gains K_p, K_i, and K_d are represented by a string of 32 binary bits. Then binary coded value is converted to decimal value which gives the corresponding gain values. Now the problem is the optimization of dynamic performance of the system with respect to undershoot, overshoot and settling time. We choose the fitness function as the sum of the absolute value of the error signal multiplied with time (ITAE). Population size is chosen as 100. The fitness function is computed for each string of the population, the string which gives less value of fitness function is considered as the better one. The better strings survive in the next population and 50 % of the strings are selected on the basis of their fitness function value and the remaining 50 % are selected from the first generation on the basis of their best value to make the population size of 100 for the next generation. After performing GA operations such as selection, cross over and mutation new off spring strings are produced for the controller gains. Then the system performance characteristics and the fitness values are evaluated for each string. The continuous process of evaluation of fitness function, selection, crossover and mutation represents one complete cycle of iteration. In such a way that within 100 iteration cycles the PID controller gains reach its optimal value to obtain the desired performance characteristics.

3.2 Particle Swarm Optimization

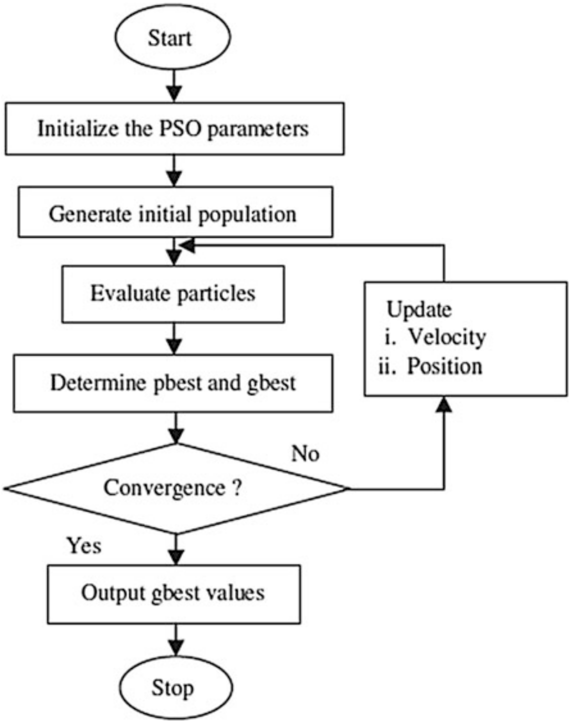
Particle Swarm Optimization (PSO) is a population based stochastic optimization technique developed by Eberhart and Kennedy [22], inspired the social behavior of bird flocking or fish schooling. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optimal by updating generations [24]. However, unlike GA, PSO has no evolution operators such as crossover and mutation. The population of solution candidates is called a "swarm", while each candidate is called a "particle". It uses a number of particles that constitute a swarm moving around in the D-dimensional search space looking for the best solution. The particles have memory and each particle keeps track of its previous best position, called *pbest* with its fitness value. When a particle takes all the population as its topological neighbors, the best value is a global best called *gbest*. The PSO concept consists of changing the velocity of each particle toward its pbest and gbest locations at every iteration. The flow chart of PSO Algorithm employing is shown in Fig. 2.

Further investigation describes the implementation of PSO algorithm in this work. Let a swarm of *n* particles be considered for population. In a physical D-dimensional search space, the position and the velocity of individual *i*th *particle is* represented as the vectors $X_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,D})$ and $V_i = (v_{i,1}, v_{i,2} \ldots v_{i,D})$ respectively. The pbest is the best previous position yielding the best fitness value for the *i*th particle and is represented as $pbest_i = (pbest_{i,1}, pbest_{i,2}, \ldots pbest_{i,D})$ and gbest is the best position in the whole swarm population and is represented as $gbest_i = (gbest_{i,1}, gbest_{i,2}, \ldots gbest_{i,D})$. The PSO algorithm updates its velocity and its position by the using the following Equation [13]:

$$V_{i,d}^{k+1} = W * V_{i,d}^{k} + c_1 * rand_1 \times (pbest_{i,d}^{k} - X_{i,d}^{k}) + c_2 * rand_2 \times \left(gbest_{i,d}^{k} - X_{i,d}^{k}\right) \quad (6)$$

$$X_{i,d}^{k+1} = X_{i,d}^{k} + V_{i,d}^{k+1} \quad (7)$$

Fig. 2 Flow chart of PSO algorithm



where $C_1 = 1.5$ and $C_2 = 1.5$ are the learning factors which determines the relative influence of cognitive and social component to update the position and velocity respectively. $rand_1$ and $rand_2$ are two random numbers in the range of [0,1]. $V_{i,d}^{k}$ and $X_{i,d}^{k}$ are the velocity and position of *i*th particle in *d*th dimension till *k*th iteration respectively. The $gbest_{i,d}^{\ k}$ is the global best of *i*th particle in *d*th dimension till *k*th iteration and $pbest_{i,d}^{k}$ is the personal best of *i*th particle in *d*th dimension till *k*th iteration. The inertia weight parameter W, which controls the exploration and exploitation of the search space. In general, the weight W is set according to the following equation [13]:

$$W = W_{max} - (W_{max} - W_{min}) \times Iter/Iter_{max} \tag{8}$$

where W_{max} and W_{min} are the initial and final weight respectively. Iter is the current iteration number and $Iter_{max}$ is maximum iteration number. The principle of a particle displacement in the swarm is graphically shown in Fig. 3, for a two dimensional design space.

The velocity is restricted to a certain dynamic range. v_{max} is the maximum allowable velocity for the particles, i.e., in case the velocity of the particle exceeds v_{max}, then it is reduced to v_{max}. Thus, the resolution and fitness of search depend upon v_{max}. If v_{max} is too high, then the particles will move beyond good solution, and if v_{max} is too low, then the particles will be trapped in local minima. The learning factors (c1 and c2) which change the velocity of a particle towards $pbest_i$ and $gbest_i$.

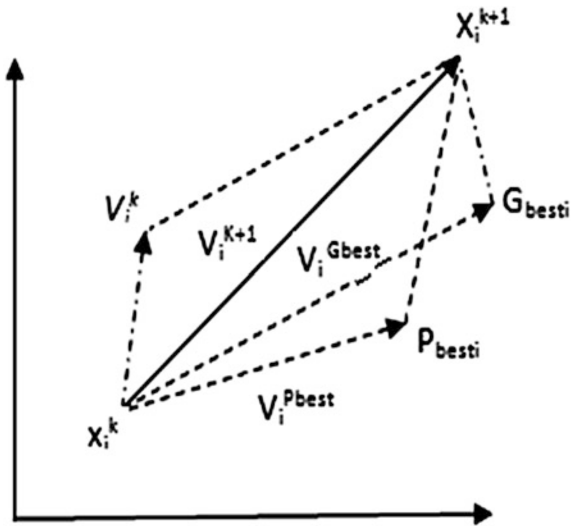


Fig. 3 Particle's position from one instant k to another instant k + 1

4 Simulation Results

Simulation studies were performed on an interconnected power system that explained in Sect. 2. Typical data for the system parameters and algorithm parameters are given in Appendix. To start GA algorithm, a decision has to be made about the GA parameters which include population size, crossover probability, mutation probability, and number of generations. The proper choice of these parameters will ensure sufficient diversity in the population, which prevents the GA from being trapped in a local minimum. Moreover, random initial population will prevent premature convergence, and does not bias the performance of the GA. General guide lines available in the literature can be used in the selection process. After so many trials, a population size, a crossover probability, and a mutation probability are used as given in Appendix are chosen. The algorithm is terminated when there is no significant improvement in the value of the performance index as shown in Fig. 4.

The PSO parameters given in Appendix are used. After updating the position and the velocity of each particle the performance index is evaluated and the convergence is verified. The algorithm is also terminated when there is no significant improvement in the value of the performance index as shown in Fig. 5.

From Figs. 4 and 5 it is clearly understand that the PSO algorithm will provide better performance in reducing the performance index value. After 30 generations only GA provides the saturated value of ITAE. But in case of PSO from initial condition also the value of ITAE is very much reduced as compared to GA.

The performances of three controllers (Conventional, GA and PSO) are tested with the power system having different combinations of units such as thermal and hydro units. The main objective of this paper is to establish that the PSO algorithm is the best optimization algorithm for complex system when there are system parameters and load changes are frequently occurred. For that different test cases in the power system at different conditions are considered Table 1 shows 18 test cases of two area interconnected power systems.

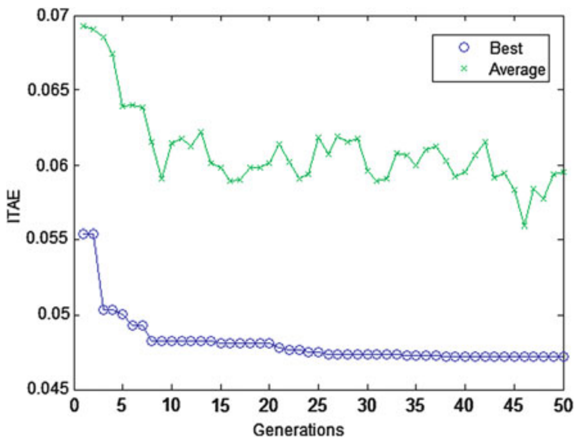


Fig. 4 Performance Index for the test case A3 using GA

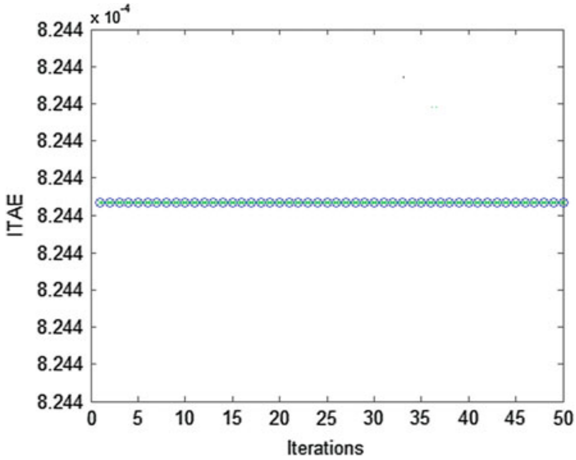


Fig. 5 Performance Index for the test case B5 using PSO

Table 1 Test cases of interconnected two-area power systems

Test case	System parameters	Area 1 Unit I	Area 2 Unit II	Load conditions
Case A1	$T_{p1} = 20;$	Thermal	Thermal	10 % increase in area 1
Case A2	$T_{12} = 0.0866$	Thermal	Thermal	25 % increase in area 1
Case A3	$B1 = 0.4166$	Thermal	Thermal	10 % increase in area 2
Case A4	$T_{p2} = 20;$	Thermal	Thermal	25 % increase in area 2
Case A5	$T_{12} = 0.0549$	Thermal	Thermal	10 % increase in area 1 and 2
Case A6	$B_2 = 0.275$	Thermal	Thermal	25 % increase in area 1 and 2
Case B1	$T_{p1} = 10;$	Thermal	Hydraulic	10 % increase in area 1
Case B2	$T_{12} = 0.0549$	Thermal	Hydraulic	25 % increase in area 1
Case B3	$B_1 = 0.275$	Thermal	Hydraulic	10 % increase in area 2
Case B4	$T_{p2} = 20;$	Thermal	Hydraulic	25 % increase in area 2
Case B5	$T_{12} = 0.0866$	Thermal	Hydraulic	10 % increase in area 1 and 2
Case B6	$B_1 = 0.4166$	Thermal	Hydraulic	25 % increase in area 1 and 2
Case C1	$T_{p1} = 10;$	Hydraulic	Hydraulic	10 % increase in area 1
Case C2	$T_{12} = 0.0549$	Hydraulic	Hydraulic	25 % increase in area 1
Case C3	$B_1 = 0.275$	Hydraulic	Hydraulic	10 % increase in area 2
Case C4	$T_{p2} = 10;$	Hydraulic	Hydraulic	25 % increase in area 2
Case C5	$T_{12} = 0.0549$	Hydraulic	Hydraulic	10 % increase in area 1 and 2
Case C6	$B_2 = 0.275$	Hydraulic	Hydraulic	25 % increase in area 1 and 2

For analyzing purpose the load in the two areas are changed as 10 and 25 % and with transient responses are observed. Simulation analytical results conclude that the PSO algorithm could rapidly converge to the best optimal solution. In this section different comparative cases are examined to show the effectiveness of the proposed PSO Algorithm method for optimizing PID controller parameters. The performance index is calculated for the given power system using various techniques are tabulated in Table 2.

Table 2 ITAE Value for various load conditions

The calculated ITAE							
Test cases	PSO	GA	CONV	Test Cases	PSO	GA	CONV
Case A1	0.0012	0.0112	0.0405	Case B4	0.0024	0.0314	0.6775
Case A2	0.0052	0.0235	0.6275	Case B5	0.0008	0.0415	0.4454
Case A3	0.0065	0.0471	0.7501	Case B6	0.0021	0.0612	0.5125
Case A4	0.0046	0.0884	0.1123	Case C1	0.0065	0.1221	0.2010
Case A5	0.0044	0.0556	0.2245	Case C2	0.0054	0.0067	0.0221
Case A6	0.0051	0.0088	0.0334	Case C3	0.0056	0.0545	0.0112
Case B1	0.0087	0.0234	0.4231	Case C4	0.0263	0.0615	0.1125
Case B2	0.0056	0.0887	0.3345	Case C5	0.0003	0.0511	0.0123
Case B3	0.0011	0.0445	0.1152	Case C6	0.0004	0.0061	0.0812

The dynamic performances of the system under varying load conditions when the system parameter changes are compared for three different controllers. For different values of ΔP_{L1} are applied to both areas, at the same time the system parameters such as T_{Pi}, T_{ij} and B_i are also changed to show the effectiveness of the control strategy optimized by the PSO Algorithm. A step load disturbance of control area 1 is increased by 10 and 25 % of nominal loading and the transient response of the system is observed. The same disturbances are applied to control area 2 and the response of the system is also observed. Then the increased load disturbance 10 and 25 % of nominal loading is applied to both areas simultaneously. As a result, it is found that the PSO based controller drastically reduces the overshoot by a large value as shown in Figs. 6, 7 and 8. Settling time, Rise Time and Peak Time have also improved. All these analytical results have been validated by executing MATLAB SIMULINK with proper values of input parameters, variable parameters and optimal PID gains.

4.1 Performance Analysis

The optimal objective function evaluations are made 50 times for each technique with all the test cases. The Matlab 7.0 software is used for simulation purpose. Figures 6, 7 and 8 shows the plots of Change in FI (DF1), Change in F2 (DF2) and Change in Ptie (Delta Ptie) versus time for all three algorithms for test cases A1, B4 and C5 respectively.

4.2 Parameter Variations

A parameter variation test is also applied to assess the robustness of the proposed controller. Figure 6 shows the response of the system with variations in T_{ij}. It is

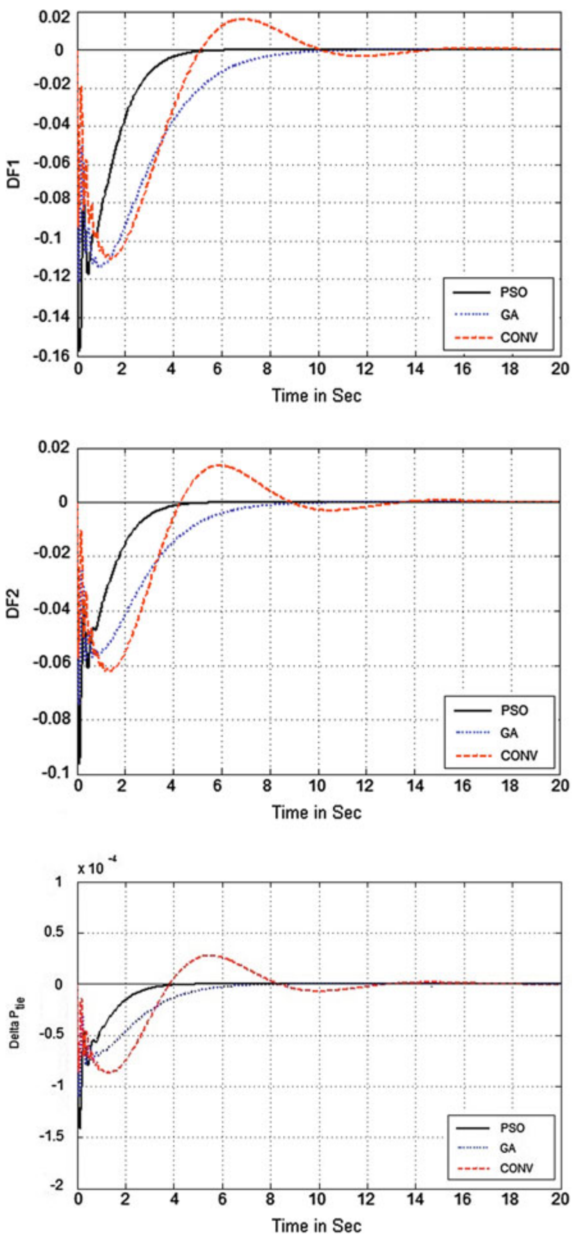


Fig. 6 Change in frequency DF1, DF2 and Tie-line power flow for the test case A1

clear that the system is stable with the proposed controller. Another parameter variation test is also applied to validate the effectiveness of the proposed controller. The response of the system with variations in generator time constant (Ti)

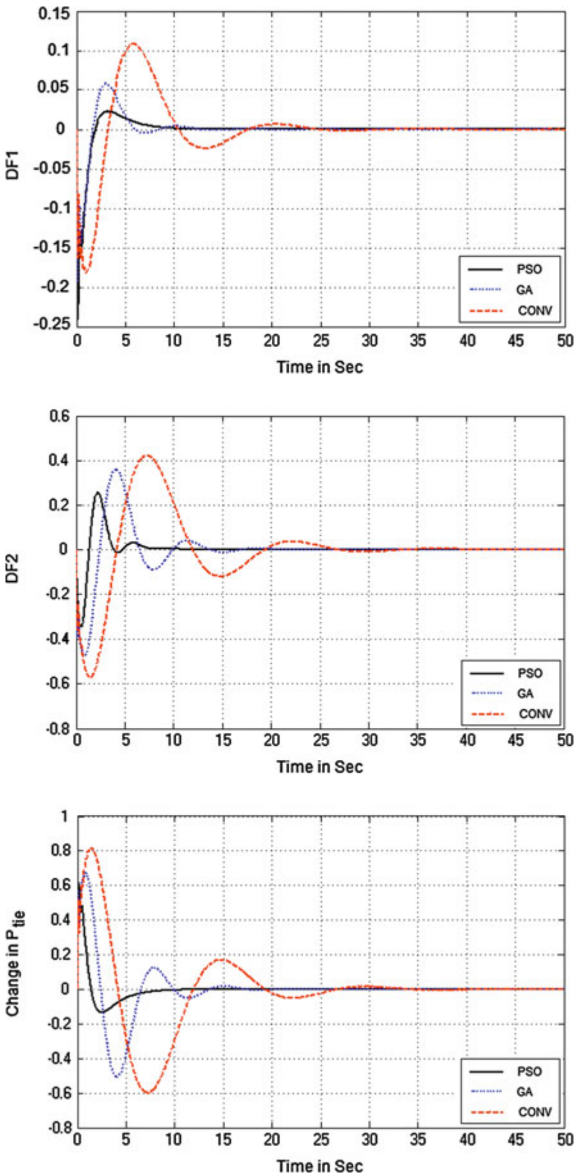


Fig. 7 Change in frequency DF1, DF2 and Tie-line power flow for the test case B4

is shown in Fig. 7. The designed controller is capable of providing sufficient damping to the system oscillatory modes under different operating conditions. Hence, the robustness of the proposed controller are verified.

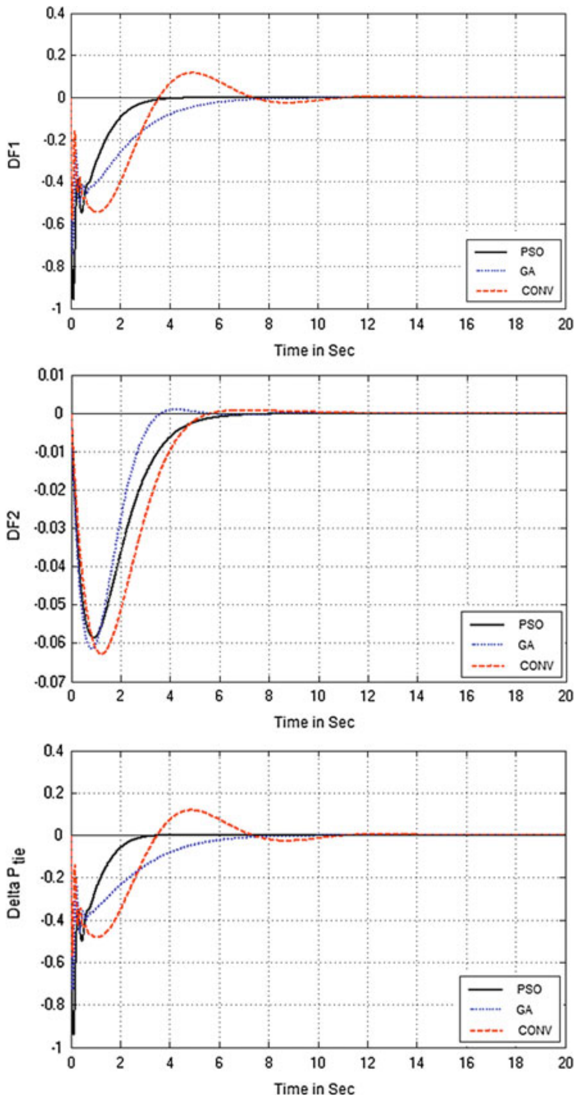


Fig. 8 Change in frequency DF1, DF2 and Tie-line power flow for the test case C5

5 Conclusions

The proposed PSO Algorithm is applied to tune the parameters of the load frequency controller in two area interconnected power systems. The proposed controller was applied to the power systems with the considerations of system parameter changes and various load conditions. To demonstrate the robustness of the proposed method, comparative study has been made between Conventional, GA and PSO controller. The optimal gain values of PID Controller are obtained by applying Genetic Algorithm while considering the ITAE as performance index. The performance measures such as the settling time, rise time, maximum overshoot, and undershoot are being observed from the response curve. The optimal gain values are also obtained using proposed PSO algorithm and it provides better performance than GA under dynamic condition. The simulation results show that the proposed method is robust when changes in the parameter of the system occurred. Therefore, the proposed PSO-PID controller is recommended to generate good quality and reliable electric energy. In addition, the proposed controller is very simple and easy to implement since it does not require more information about system parameters. Many real world optimization problems can be modeled with multiple and even conflicting objectives. Hybrid metaheuristics technique can provide a more efficient behavior and a higher flexibility when dealing with multi objective problems. In future, multi objective design of load frequency controller using hybrid metaheuristics technique will be considered.

6 Appendix

The typical values of parameters of the system are shown below:

$$\mathrm{TP}_1 = \mathrm{TP}_2 = 20\ \mathrm{s};\ \mathrm{T}_{\mathrm{T1}} = \mathrm{T}_{\mathrm{T2}} = 0.3\ \mathrm{s};\ \mathrm{T}_{12} = 0.545\ \mathrm{p.u};$$
$$\mathrm{T}_{\mathrm{G1}} = \mathrm{T}_{\mathrm{G2}} = 0.08\ \mathrm{s};\ \mathrm{Kp}_1 = \mathrm{Kp}_2 = 120\ \mathrm{Hz/p.u\ MW};\ \mathrm{a12} = -1;$$
$$\mathrm{R1} = \mathrm{R2} = 2.4\ \mathrm{Hz/p.u\ MW};\ \mathrm{B}_1 = \mathrm{B}_2 = 0.425\ \mathrm{p.u\ MW/Hz};$$

GA Parameters:

No of variables = 3; No of generation = 50;
Population size = 20; Cross over probability = 0.6;
Mutation probability = 0.06.PSO Parameters:

Population Size = 20; $C_1 = C_2 = 2$; $\mathrm{rand}_1 = \mathrm{rand}_2 = 0.5$;
$\omega_{\max} = 0.9$ and $\omega_{\min} = 0.4$; $\mathrm{Iter}_{\max} = 50$.

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