

# Evolutionary computation based three-area automatic generation control

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## ARTICLE INFO

### Keywords:

AGC

Evolutionary techniques

SFL

## ABSTRACT

In this paper, various novel heuristic stochastic search techniques have been proposed for optimization of proportional–integral–derivative gains used in Sugeno fuzzy logic based automatic generation control of multi-area thermal generating plants. The techniques are genetic algorithm, various types of particle swarm optimization and bacteria foraging optimization. Numerical results show that all optimization techniques are more or less equally very effective in yielding optimal transient responses of area frequency and tie-line power flow deviations, but still MCASO and BFO yield much more global true optimal results. Particle swarm optimizations take the least time to achieve the same optimal gains. These gains are for nominal system parameters. For varying off-nominal on-line system parameters, fast acting Sugeno fuzzy logic manipulates the nominal gains adaptively to determine transient responses.

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## 1. Introduction

Automatic generation control (AGC) is a very important issue in power system operation and control for supplying sufficient and reliable electric power with good quality.

The first attempt to control the frequency is via the flywheel governor of the synchronous machine. This governor's action is insufficient and imposition of a supplementary control action, i.e. supplementing the governor by a signal proportional to the integral of the frequency deviation from its normal value, has been proved to be successful in achieving zero steady state frequency deviation. But it exhibits a poor dynamic performance as evidenced by large overshoot and transient frequency deviation (Concordia & Kirchmayer, 1954; Elgerd, 2001; Kirchmayer, 1958; Kothari & Dhillon, 2004; Wood & Woolenberg, 1984). Moreover, the settling time is relatively more. Several attempts have been made to enhance the performance of the integral controller by supplementing its action or by reformulating the control problem according to a dynamic concept of automatic tie-line power and frequency control of two interconnected areas. Significant work in classical approach appeared in literature (Cohn, 1961; Cohn, 1971; Concordia, Kirchmayer, & Szymanski, 1957; Elgerd & Fosh, 1970; Moran & Williams, 1968; Williams, 1974) from 1961 to 1974. An area frequency response characteristic (AFRC) is used with integral form of control to reduce the frequency and tie-line error to zero in steady state due to a load change  $\Delta P_D$  in any area. In Elgerd and Fosh (1970), the authors developed a dynamic system model of the multi-area electric energy system suitable for study of the megawatt-frequency control problem. Classical optimization theory was used to find the best value of  $K_i$  gain of the area control error (ACE) integrator, and  $b$ , frequency bias, in the sense of minimizing the integral square error (ISE) criterion. Williams (1974) commented on the value of frequency bias based on sensitivity analysis that it depends upon the time constants of the system components.

The linear optimal control theory developed by control engineers has now been widely used for designing feedback controllers: The theory is well documented in control literatures (Athans & Falb, 1966; Sage, 1968). In 1970, Elgerd and Fosh (1970), Fosh and Elgard (1970) first designed the LFC controller using this theory. The optimal control law is derived by the solution of algebraic Riccati equation as discussed in literature (Athans & Falb, 1966; Sage, 1968; Yu, Vongsuriya, & Wedman, 1970). Different research experts in literatures (Calovic, 1972; Cavin, Budge, & Rasmussen, 1971; Elangovan & Kuppurajulu, 1972; Fosh & Elgard, 1970; Kosut, 1970; Miniesy & Bohn, 1972; Moussa & Yu, 1972; Murthy & Ramana Rao, 1977; Nanda & Kaul, 1978; Ramana Rao & Murthy, 1979; Saha & Ghoshal, 1986; Taylor, Lee, & Dave, 1979; Tripathy & Saha, 1980; Tripathy, Hope, & Malik, 1982) have discussed the determination of optimal control law for LFC problem.

Calovic (1972) distinguished the steady state problem from the transient problem. He adjoined the integral of ACE to the system equations, which was included in performance index. As a result, all areas capable of doing so derived their area control error (ACE) to zero in steady state provided the system is stable.

Nanda and Kaul (1978) investigated the LFC problem of a two-area reheat thermal system considering generator rate constraint (GRC). They concluded that in presence of GRC optimum integral

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## Nomenclature

$ACE_i$	area control error of $i$ th area	$T_t$	non-reheat time constant
$b_i$	frequency bias coefficient of $i$ th area	$T_r$	reheat time constant
$\Delta f_i$	frequency error of $i$ th area	$c$	reheat parameter
$\Delta P_{tie_{ij}}$	tie-line power flow error between $i$ th area and $j$ th area	$K_p$	power system gain constant
$K_{Pi}$	proportional gain of PID controller	$\Delta P_{Di}$	incremental load change in area $i$
$K_{Ii}$	integral gain of PID controller	CF	constriction factor
$K_{Di}$	derivative gain of PID controller	CFA	constriction factor approach
$t_p$	area time constant	$C_1, C_2$	constant parameters of PSO
$b$	frequency bias coefficient	$pbest_i$	personal best of $i$ th particle $s_i^k$
apf_matrix	ACE participation factor matrix	gbest	group best in the population of particles
$\alpha_{12}, \alpha_{13}, \text{ and } \alpha_{23}$	ratios of areas' power ratings	cpf_matrix	contract participation factor matrix
$R$	governor regulation	LFC	load-frequency control
$T_g$	governor time constant		

gain setting was much lower as compared to the unconstrained optimum integral gain setting.

Murthy and Ramana Rao (1977) discussed the effect of variation of power system parameters on the optimal control of LFC problem and established the need for system identification from time to time for any realistic on-line control of power system.

Tripathy et al. (1982) demonstrated that the governor dead-band nonlinearity had a destabilizing effect on the load-frequency control of a power system.

In recent years digital controllers are gaining popularity in automatic generation control. This is due to the fact that digital control is more accurate and reliable, compact in size, less sensitive to noise and drift. It can be implemented in a timeshared fashion by using the computer systems in load dispatch center. The area control error (ACE), which is used in the digital controller, is obtained in discrete form by sampling operation between the system and the controller. The control vector in the discrete mode is constrained to remain constant between the sampling instants. The control problem is analyzed using discrete analysis techniques for optimization of the LFC strategy. The discrete time behavior of the continuous time system is modeled by the first order differential equations. The technique is well documented in the literature (Chan & Hsu, 1981; Geromel & Peres, 1985; Hiyama, 1982; Hiyama, 1982; Indulkar, 1992; Kumar & Malik, 1984; Kumar, Malik, & Hope, 1985; Kumar, Malik, & Hope, 1987; Kothari, Satsangi, & Nanda, 1981; Kothari, Nanda, Kothari, & Das, 1989; Kothari, Nanda, Kothari, & Das, 1992; Nanda & Kothari, 1990; Nanda, Kothari, & Satsangi, 1983).

Hiyama (1982), Hiyama (1982) proposed a method of designing discrete type load-frequency regulators of a two-area reheat type thermal system with generation-rate constraint.

Nanda et al. (1983) developed a linear discrete-time state space model for a two-area hydrothermal system. The authors stated that the maximum frequency deviation in any area out of the two was more due to a step-load perturbation in the remote area than any similar perturbation in its own area. Also the optimum integral gain settings obtained in the continuous mode AGC were not acceptable in the discrete mode.

Kumar and Malik (1984) proposed two models for discrete analysis of load-frequency control problem. In the first model the controller was in the discrete domain and power system was in continuous domain. In Chan and Hsu (1981), Kumar et al. (1985), Kumar et al. (1987), Geromel and Peres (1985), Kothari et al. (1981) discrete mode control was discussed.

Kothari et al. (1989), Kothari et al. (1992) proposed the concept of new area control error (ACEN) for AGC of interconnected power system. AGC based on ACEN regulates conventional area control error (ACE), time error and inadvertent interchange accumulations to

zero simultaneously. The problem was solved using discrete time analysis. The investigations reveal that the optimum value of inadvertent interchange bias setting is independent of GRC. With new area control error, presence of GRC deteriorated the dynamic performance.

Indulkar (1992) applied sampled data theory using z-transform to load-frequency control problem and has shown the frequency deviation and tie-line power deviation are quite different from those obtained when these error signals are assumed to be measured continuously.

Successful applications of self-tuning regulators to LFC problem were reported in literature (Aly, Abdel-Magid, & Wali, 1984; Kanniah, Tripathy, Malik, & Hope, 1984; Pan & Liaw, 1989; Sheirah & Abd, 1984; Swain & Mohanty, 1994; Yamshita & Miyagi, 1989).

Wang, Zhou, and Wen (1994) proposed a new robust adaptive load-frequency controller to improve power system performance. The standard robust control approach, Riccati equation approach and adaptive model reference control were combined to design a robust adaptive controller for a power system with parametric uncertainties. The authors demonstrated that the proposed load-frequency controller could achieve good performance even in the presence of the generation-rate constraint (GRC).

Rubaai and Udo (1994) investigated a multilevel adaptive algorithm based on a relatively fast implicit STR for multi-area power systems. The application of the proposed algorithm was suggested as a suitable alternative to the integral control used normally for the LFC.

Urn, Wang, and Zhou (1996) proposed a robust decentralized load-frequency controller (RDLFC) based on the Riccati equation approach for multi-area power system with parametric uncertainties.

The neural technology offers many more benefits in the area of nonlinear control problems, particularly when the system is operating over the nonlinear operating range. The applications of neural networks in power system control were witnessed in (Ahmed, Rao, & Sastry, 2002; Chaturvedi, Satsangi, & Kalra, 1999; Douglas, Green, & Kramer, 1994; Demiroren, Sengor, & Zeynelgil, 2001; Demiroren, Zeynelgil, & Sengor, 2001; Franoise, Magid, & Bernard, 1994; Indulkar & Raj, 1995; Sengor, Demiroren, & Zeynelgil, 2002).

LFC system performance was evaluated with a nonlinear neural network controller using a generalized neural structure to yield better system dynamic performance than the individual neurons (Chaturvedi et al., 1999).

Demiroren, Sengor et al. (2001) proposed an application of layered artificial neural network controller to study load-frequency control problem in power system. The authors concluded that the ANN configuration using back propagation through-time algorithm applied for load-frequency control at the power system

gives good dynamic response with respect to conventional controller.

The fuzzy logic control concept departs significantly from traditional control theory that is essentially based on mathematical models of the controlled process. Instead of deriving a controller via modeling the controlled process quantitatively and mathematically, the fuzzy control methodology tries to establish the controller directly from domain experts or operators who are controlling the process manually and successfully. Recently many studies exploiting the fuzzy logic concept in AGC regulator design dealing with various system aspects have appeared in the literature (Chown & Hartman, 1998; Ghoshal, 2003; Ghoshal, 2004; Gegov & Frank, 1995; Ghoshal & Goswami, 2003; Indulkar & Raj, 1995; Talaq & Al-basri, 1999).

Most recent contributions considering the problem of decomposition of multivariable systems for the purpose of distributed fuzzy control was reported by Gegov and Frank (1995). The proposed decomposition method has reduced the number of interactive fuzzy relations among subsystems.

Talaq and Al-basri (1999) have proposed an adaptive fuzzy gain scheduling scheme for conventional PI and optimal load-frequency controllers. The proposed adaptive fuzzy controller offers better performance than fixed gain controllers at different operating conditions.

Ghoshal (2003, 2003, 2004) has presented a self-adjusting fast acting fuzzy gain scheduling scheme for conventional integral gain automatic generation controller for a radial and ring connected three equal power system areas.

Ghoshal (2004) has proposed an application of a new BGA/BGA-SA based fuzzy automatic generation control of a multi-area thermal generating system. The scheme is capable of evaluating the

fitness of BGA/hybrid BGA-SA optimization by selecting a function like “figure of demerit”, which directly depends on transient performance characteristics like settling times, undershoots overshoots, and time derivative of frequency. The hybrid BGA-SA technique yields more optimal gain values than the BGA technique.

Abdel-Magid and Dawound (1997) have investigated the optimum adjustment of the classical AGC parameters for two-area non-reheat thermal system using genetic techniques. A reinforced BGA has been proposed as an appropriate optimization method to tune the membership functions and rule sets for fuzzy gain scheduling of load-frequency controllers of multi-area power systems to improve the dynamic performance. The proposed control scheme incorporates dead-band and generation-rate constraints also.

Al-Hamouz and Al-Dowaish (2000) has proposed genetic techniques (BGA) for the selection of the variable structure controller (VSC) feedback gains. The application of the proposed method to the LFC problem reveals that not only the system performance is highly improved but also the control effort is dramatically reduced.

More recently, Ghoshal (2004) has proposed application of hybrid of BGA and particle swarm optimization for optimization of PID Gains in a multi-area thermal reheat generating system and shown optimal transient response characteristics much better than those obtained by BGA and BGA-SA.

From the literature survey, it may be concluded that there is still scope of work on the optimization of PID controller parameters to further improve the AGC performance. Much better global solutions may be searched for. For this, various novel evolutionary optimization techniques are proposed and tested for comparative optimization performance study. The succeeding sections of this chapter will be concentrated on the application of evolutionary

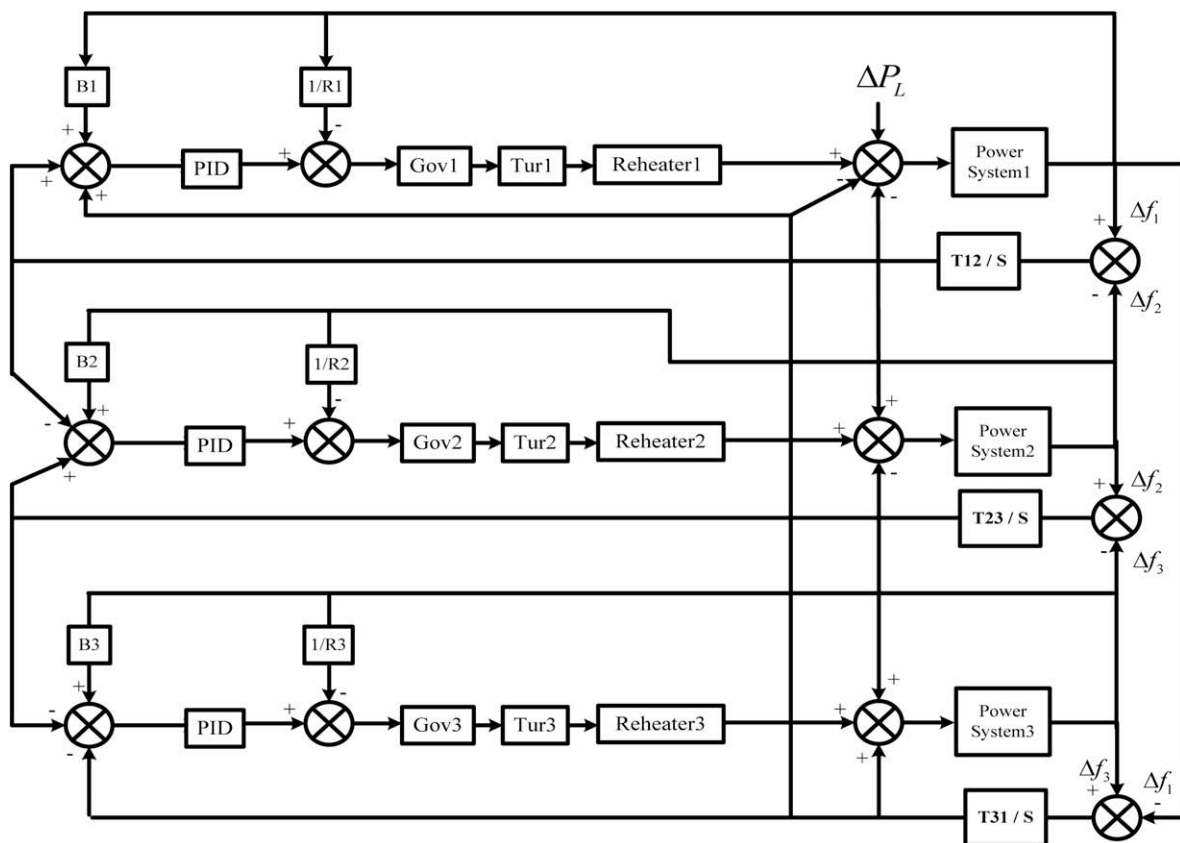


Fig. 1. MATLAB-SIMULINK based closed loop PID controlled ring connected three equal rating reheat thermal area block diagram.

optimization techniques for optimal AGC performance of an interconnected three thermal reheat generating system.

Automatic generation control of multi-area interconnected thermal generating system means zeroing of the integral area control error of each area, so that system frequency and tie-line power flows are maintained at their scheduled values. Block diagrams of incremental tie-line power out of any area and closed loop controlled system model of reheat type three-area thermal generating systems are shown in Fig. 1.

$$ACE_i = \sum_j (\Delta P_{tie,i,j} + b_i \Delta f_i) \quad (1)$$

$ACE_i$  is area control error of  $i$ th area,  $b_i$  is frequency bias coefficient of  $i$ th area,  $\Delta f_i$  is frequency error of  $i$ th area,  $\Delta P_{tie,i,j}$  is tie-line power flow error between  $i$ th area and  $j$ th area. The PID control of  $ACE_i$  over a given time interval  $\tau$  in Laplace domain is defined by:  $(-G_i(s)) \times ACE_i(s)$ , where  $G_i(s) = K_{Pi} + (K_{Ii}/s) + K_{Di} \times s$  and  $K_{Pi}$ ,  $K_{Ii}$  and  $K_{Di}$  are proportional, integral and derivative gains, respectively. The varying system input parameters are area time constant ( $t_p$ ), tie-line synchronizing coefficient ( $t_{12}$ ) and frequency bias coefficient ( $b$ ).

## 2. Description of the system model

Fig. 1. show the closed loop PID controlled ring connected three equal rating reheat thermal area block diagram. The gains in the system model may be optimal nominal gains determined off-line by various optimization techniques individually or off-nominal, on-line ones determined by fast acting Sugeno Fuzzy Logic (SFL) with off-nominal input parameters using optimal nominal gains.

True optimal nominal performance for nominal input parameters ( $t_p$ ,  $t_{12}$  &  $b$ ) means minimum undershoot (USH), minimum overshoot (OSH) and minimum settling time ( $t_s$ ) of  $\Delta f_1$ ,  $\Delta f_2$  and  $\Delta f_3$  of area1, area2 and area3, respectively. This is achieved through optimization of PID Gains of the PID controllers by any of the optimization techniques. This optimization really corresponds to minimization of an objective function which in this work, is defined as the figure of demerit as follows:

$$\text{Figure of demerit} = (\text{overshoot} \times \sigma)^2 + (\text{undershoot} \times \rho)^2 + (\text{settling time})^2 \quad (2)$$

These values are computed by first sampling the transient response curve of  $\Delta f_1(t)$ . Number of samples chosen as 400 has become sufficient for good accuracy because maximum settling time as seen from the curve rarely exceeds 100 s. After sampling, the magnitudes of the samples are checked to be more than or equal to 0.0001 pu, reckoning from the last sample where the magnitude is very much less than 0.0001 pu. The instant of time when the above condition is satisfied is in our case called to be the settling time. Undershoot and overshoot are nothing but the minimum or the maximum values of the samples, respectively. Because overshoot and undershoot values are very small compared with settling time, large multipliers  $\sigma$  and  $\rho$  weight these so that these low values may compete with reduction of settling time during any optimization process. In this work, the best selected values of  $\sigma$  and  $\rho$  are 1000 and 100, respectively. Impact of minimization is more on overshoot than on initial undershoot. It is found that the latter does not reduce much even with higher weighting factor. The total system is a non minimum phase system.

By any of the optimization techniques nominal optimal PID gains are determined for various nominal parameter sets. These optimal PID gains will result in true optimal nominal transient performance of the system for nominal parameters. For off-nominal input parameters off-nominal PID gains are obtained by applying Sugeno Fuzzy Logic as subsequently explained. These off-nominal

optimal PID gains will result in off-nominal optimal transient performance of the system for off-nominal parameters.

## 3. Evolutionary techniques employed

The present work incorporates various kinds of evolutionary computation techniques for optimization. The following optimization techniques are used in the present work. The details of all techniques are explained in Roy (2008). Still MCASO and BFO require special details because these two techniques finally prove to be the best and near best, respectively, for the present work.

1. Binary coded genetic technique (BGA)
2. Real coded genetic algorithm (RGA)
3. Genetic algorithm combined with simulated annealing (BGA-SA)
4. Evolutionary programming (EP)
5. Hybrid evolutionary programming (HEP)
6. Particle swarm optimization (PSO)
  - (a) Classical particle swarm optimization (CPSO)
  - (b) Hybrid particle swarm optimization with inertia weight approach (HPSOIWA)
  - (c) Hybrid particle swarm optimization with constriction factor approach (HPSOCFA)
  - (d) Evolutionary particle swarm optimization (EPSO)
  - (e) New particle swarm optimization (NPSO)
  - (f) Velocity update relaxation momentum factor induced particle swarm optimization (VURMFPSO)
  - (g) Craziness based particle swarm optimization (CRPSO)
  - (h) Particle swarm optimization with constriction factor approach with Taguchi selection (HPSOCFA-Taguchi)
  - (i) Modified chaotic ant swarm optimization (MCASO)

Chaotic ant swarm optimization (CASO) (Cai et al., 2007) combines the chaotic and self organization behavior of ants in the foraging process. It includes both effects of chaotic dynamics and swarm-based search. The algorithm has been employed to tune the PID controller parameters of the three-area power system. CASO is based on the chaotic behavior of individual ant and the intelligent organization actions of ant colony. Here, the search behavior of the single ant is “chaotic” at first, and the organization variable  $r_i$  is introduced to achieve self organization process of the ant colony. Initially, the influence of the organization variable on the behavior of individual ant is sufficiently small. With the continual change of organization variable evolving in time and space, the chaotic behavior of the individual decreases gradually via the influence of the organization variable and the communication of previously best positions with neighbors, the individual ant alters his position and moves to the best one it can find in the search space. According to the distance between ant and their neighbors, a definition of neighbor (dbest) is introduced, in order to simulate the behaviors of ants in nature.

The searching area of ants corresponds to the problem search space. In the search space  $R^l$ , this is the  $l$ -dimensional continuous space of real numbers, the algorithm searches for optima. A population of  $K$  ants is considered. These ants are located in a search space  $S$  and they try to minimize a function  $f: S \rightarrow R$ . Each point  $s$  in  $S$  is a valid solution to the considered problem. The position of an ant  $i$  is assigned the algebraic variable symbol  $S_i = (z_{i1}, \dots, z_{il})$ , where  $i = 1, 2, \dots, K$ . Naturally each variable can be of any finite dimension. During its motion, the organization processes of the swarm influence each individual ant. In mathematical terms, the strategy of movement of a single ant is assumed to be a function of the current position; the best position found by itself and any member of its neighbors and the organization variable is given by (4).



$$y_i(n) = y_i(n-1)^{1+r} \quad (3)$$

$$z_{id}(n) = \left( z_{id}(n-1) + \frac{c}{\psi_d} V_i \right) \exp((1 - \exp(-ay_i(n))) \left( 3 - \psi_d \left( z_{id}(n-1) + \frac{c}{\psi_d} V_i \right) \right) - \frac{c}{\psi_d} V_i + \exp(-2ay_i(n) + b)(p_{id}(n-1) - z_{id}(n-1)) \quad (4)$$

The initial value of  $z_{id}(0)$  are chosen within the limits of the variables, where

$n$	Current iteration cycle,
$n-1$	Previous iteration cycle,
$y_i(n)$	Current state of the organization variable ( $y_i(0) = 0.999$ ),
$a, b, c$	Positive constants, $a = 200$ , $0 \leq b \leq \frac{2}{5}$ , $c = 7.5$ ,
$r_i \in [0, 0.1]$	A positive constant, and is termed as the organization factor of ant $i$ ,
$z_{id}(n)$	Current state of the $d$ th dimension of the individual ant $i$ , $d = 1, 2, \dots, l$ ,
$\Psi_d$	Determines the selection of the search range of $d$ th element of variable in the search space, $\Psi_d > 0$ ,
$V_i$	Determines the search region of $i$ th ant and offers the advantage that ants could search diverse regions of the problem space ( $V_i = \text{rand}()$ ).

CASO is modified as MCASO with the introduction of craziness to the movement of the ants. Introduction of craziness enhances MCASO's ability of searching and convergence to a global optimal solution. Variables' upper and lower bound restrictions are always present. Ultimately, after maximum iteration cycles the optimal solution of  $z_{id}$  corresponds to global optimal value of fitness function under consideration.

The neighbor selection can be defined in the following two ways. The first one is the nearest fixed number of neighbors. The nearest  $m$  ants are defined as the neighbors of single  $i$ th ant. The second way of the number of neighbor selection is to consider the situation in which the number of neighbors increases with iteration cycles. This is due to the influence of self-organization behavior of ants. The impact of organization will become stronger than before and the neighbors of the ant will increase. That is to say, the number of nearest neighbors is dynamically changed as iteration progresses.

The general CASO is a self-organizing system (Cai et al., 2007). When every individual trajectory is adjusted toward the successes of neighbors, the swarm converges or clusters in optimal regions of the search space. The search of some ants will fail if the individual cannot obtain information about the best food source from their neighbors.

While dealing with PID tuning, the algorithm's parameters  $r_i$ ,  $\Psi_d$ ,  $V_i$ ,  $a$ ,  $b$ ,  $c$  are different from those of Cai et al. (2007). These are respectively,  $1 + r_i$  is replaced by  $(1.02 + 0.04 \times \text{rand}(1))$ ,  $\Psi_d = 1.75$ ,  $V_i = \text{rand}(1)$ ,  $a = 1$ ,  $b = 0.1$ ,  $c = 3$ . These values are pre-set after a lot of experimentation to get the best convergence to optimal solution. In this work, as similar to CRPSO, craziness in velocity is also introduced as given below.

$$z_{id}(n) = z_{id}(n) + \text{sign}(r4) \times v_i^{\text{craziness}} \quad (5)$$

The value of  $\text{sign}(r4)$  will be determined by (5).

### 3.1. Bacterial foraging optimization (BFO)

Natural selection favors propagation of genes of those animals that have efficient *foraging strategies* (method of finding, handling, and taking in food) and eliminate those animals that have weak foraging strategies. As the efficient foraging strategy allows the

animals to ingest better and quality food, only animals having better food searching strategy are allowed to enjoy reproductive cycle in turn producing better species. Poor foraging strategies are either shaped into good ones or eliminated after many generations. With their own physiological (e.g. cognitive and sensing capabilities) and environmental (e.g. physical characteristics of the search space, density of prey, risk and hazards from predators) constraints, animals try to maximize the consumption of energy per unit time interval. Such evolutionary idea has bred the concept of BFO (Passino, 2002) as an optimization technique. The interested research groups are gradually utilizing it as an optimization technique to solve a range of nonlinear optimization problems.

Four processes can explain the foraging strategy of *Escherichia* bacteria present in human intestine. These are *chemotaxis*, *swarming*, *reproduction*, and *elimination-dispersal*.

A set of relatively rigid flagella helps the bacteria in locomotion. Its characteristics of movement for searching of food can be in two different ways, i.e. swimming and tumbling together known as *chemotaxis*. Its movement in a predefined direction is termed as *swimming* (*running*), where as *tumbling* is the movement in altogether different direction. During its entire lifetime, it alternates between these two modes of operation. Clockwise rotation of its flagella results in *tumble*, where as, anticlockwise rotation yields *swim*.

Likelihood of increased search for nutrient concentration, enhanced capability to gang up on a large prey to kill and digest it, group protection of the individual from predators are the highlighting objectives and motivations of social and intelligent foraging strategy. Successful foraging for food of each and individual of the group results from grouping, communication mechanism and collective intelligence is utilized. To attract the other bacteria towards the optimal convergence direction, it is necessary to pass on the information about the nutrient concentration (optimal point) to other bacteria. This is called *swarming*. To achieve this, a penalty function based upon the relative distances of each bacterium from the fittest bacterium till that search duration, is added to the original optimization function. This penalty function becomes zero when all the bacteria have merged into the desired solution point.

After getting evolved through several *chemotactic* stages, the original set of bacteria is allowed for *reproduction*. Biological aspect of their conjugation process is splitting of one into two identical bacteria. It is mimicked in the optimization process by replacing the poorer half (having higher objective (figure of demerit) function value for minimization problem and vice versa) with weaker foraging strategy by the healthier half, which is eliminated owing to their poorer foraging strategy, maintaining the total number of population of bacteria constant in the process of evolution.

*Elimination* and/or *dispersal* of a set of bacteria to a new position result in drastic alteration of smooth biological process of evolution. The underlying concept behind this step is to place a newer set of bacteria nearer to the food location to avoid *stagnation* (to avoid premature trapping into local optima).

The process of BFO based optimization as adopted in the present work is detailed below.

#### Step 1: Initialization

- Maximum reproduction cycle,  $\text{max}_{\text{reprod}} = 10$
- Maximum chemo tactic cycle,  $\text{max}_{\text{chemo}} = 20$
- Maximum dispersal cycle,  $\text{max}_{\text{dispersal}} = 2$
- Total number of bacteria,  $\text{numBact} = 500$
- Maximum number of iteration cycle ( $k$ ),  $\text{max}_{\text{cycles}} = 800$
- Some positive constants  $d_{\text{attract}} = 2.0$ ;  $w_{\text{attract}} = 0.2$ ;  $d_{\text{repellent}} = 2.0$ ;  $w_{\text{repellent}} = 0.1$ ; selection ratio,  $s_r = 0.5$ ; probability of elimination,  $P_{\text{ed}} = 0.3$ ;  $c_{\text{max}} = 0.1$ ;  $c_{\text{min}} = 0.0001$ ;  $d_1 = 0.00001$ ;  $d_2 = 0.00001$ .
- Maximum swim length (integer value)  $\text{max}_{\text{swim}} = 4$
- Number of problem variables, var

- (i) Variables' upper and lower limits  $\text{var}_{\max}$  and  $\text{var}_{\min}$ , respectively, as given for individual test objective function.

**Step 2:** Compute fitness functions of the bacteria,  $J$

**Step 3:** Find pseudo global optimum fitness

**Step 4:** Find global optimum bacteria and its variables

**Step 5:** Swarming:

$$J_{\text{bact}}^{(k)} = J_{\text{bact}}^{(k)} - \sum_{\text{numBact}} d_{\text{attract}} \times \left( e^{-W_{\text{attract}} \times \sigma_{\text{bact}}^{(k)}} \right) + \sum_{\text{numBact}} h_{\text{repellent}} \times \left( e^{-W_{\text{repellent}} \times \sigma_{\text{bact}}^{(k)}} \right) \quad (6)$$

where,

$$\sigma_{\text{bact}}^{(k)} = \sigma_{\text{bact}}^{(k)} + \sum_{\text{numBact}} \left( \text{var}_{\text{global}}^{(k)} - \text{var}_{\text{bact}}^{(k)} \right)^2 \quad (7)$$

**Step 6:** Tumbling:

$$(a) \Delta^{(\text{var})} = (2 \times \text{rand}(\text{rand}()) - 1) \times \text{rand}() \quad (8)$$

$$\Delta\Delta = \sqrt{\Delta(\text{var}) \times \Delta'(\text{var})} \quad (9)$$

$$(b) \text{ Compute : } \text{var}^{(k+1)} = \text{var}^{(k)} + (c_{\max} - d_2) \times \frac{\Delta^{(\text{var})}}{\Delta\Delta} \quad (10)$$

**Step 7:** Impose limits of variables

**Step 8:** To start with BFO the following pseudo codes are to be followed for  $\text{disperse} := 1$  to  $\text{max}_{\text{disperse}}$  do for  $\text{reprod} := 1$  to  $\text{max}_{\text{reprod}}$  do for  $\text{chemo} := 1$  to  $\text{max}_{\text{chemo}}$  do

$$c^{(\text{var})} = c_{\max}^{(\text{var})} - (c_{\max}^{(\text{var})} - c_{\min}^{(\text{var})}) \times \frac{\text{cycle}}{\text{max cycles}} \quad (11)$$

**Step 9:** Compute fitness functions of the bacteria,  $J$

**Step 10:** Find pseudo global optimum fitness  $J_{\text{global}}$

**Step 11:** Swarming: As shown in Step 5

**Step 12:** Swarming of each bacteria

- (a) for  $\text{bact} := 1$  to  $\text{numBact}$  do

$m_{\text{swim}} = 0$

- (b) while  $m_{\text{swim}} < \text{swimlength}$

$m_{\text{swim}} = m_{\text{swim}} + 1$

- (c) if  $J_{\text{bact}}^{(k)} < J_{\text{bact}}^{(k-1)}$   
 $xx = \text{'swim'}$   
 Compute  $\Delta^{(\text{var})}$ ,  $\Delta\Delta$  using (8) and (9)

$$\text{Compute } \text{var}^{(k)} = \text{var}^{(k)} + (c^{(\text{var})} + d_1^{(\text{var})}) \times \frac{\Delta^{(\text{var})}}{\Delta\Delta} \quad (12)$$

Impose variable(s) value(s)' restrictions

Compute  $J_{\text{bact}}$  of each bacterium

Swarming: As shown in Step 5

End of (c): else

$xx = \text{'Tumble'}$

$J_{\text{bact}}^{(k)} < J_{\text{bact}}^{(k-1)}$   
 $m_{\text{swim}} = \text{swimlength}$

Compute  $\Delta^{(\text{var})}$ ,  $\Delta\Delta$  using (8) and (9)

$$\text{Compute } \text{var}^{(k)} = \text{var}^{(k)} + (c^{(\text{var})} - d_2^{(\text{var})}) \times \frac{\Delta^{(\text{var})}}{\Delta\Delta} \quad (13)$$

Impose variable(s) value(s)' restrictions

Compute  $J_{\text{bact}}$  of each bacterium

Swarming: As shown in Step 5

End of if loop (c)

End of while loop (b)

End of for loop (a)

**Step 13:** Swarming: As shown in Step 5

Impose variable(s) value(s)' restrictions

End of chemo loop

**Step 14:** Selection and copying of elite bacteria

Select elite bacteria by  $s_r$  ratio and copy the elite set of bacteria over the non-elite bacteria

Impose variable(s) value(s)' restrictions

End of reprod loop

End of disperse loop

**Step 15:** Compute global optimum fitness value among all previous pseudo global optimum fitness values and plot. Determine corresponding optimum problem variables.

#### 4. Brief overview of Sugeno Fuzzy Logic as applied to PID gain scheduling

The whole process (Ghoshal, 2003; Ghoshal, 2004; Ghoshal, 2004; Ghoshal & Goswami, 2003) involves three steps as:

- (a) *Fuzzification* of input parameters  $t_p$ ,  $t_{12}$  and  $b$  in terms of fuzzy subsets like "Small (S)", "Medium (M)", and "Large (L)" associated with overlapping (between "S" & "M" or "M" & "L") triangular membership functions. The respective nominal central values of the subsets of  $t_p$  are (10, 0.145, and 0.125), those of  $t_{12}$  are (20, 0.345, and 0.275) and those of  $b$  are (30, 0.545, and 0.425), respectively, at which membership values is unity. These are nominal system parameters also. Sugeno fuzzy rule base table consists of  $3^3$  logical input sets, each composed of three nominal parameters. Each input set corresponds to nominal optimal PID gains as output.
- (b) *Sugeno Fuzzy Inference*: For on-line imprecise values of input parameters, firstly their subsets in which the values lie are determined with the help of "IF", "THEN" logic and corresponding membership values are determined from the membership functions of the subsets. From Sugeno Fuzzy Rule Base Table, corresponding input sets and nominal PID gains are determined. Now, for each input set being satisfied, three membership values like  $\mu_{tp}$ ,  $\mu_{t12}$  and  $\mu_b$  and their minimum  $\mu_{\min}$  are computed. For the input logical sets, that are not satisfied because parameters do not lie in the corresponding fuzzy subsets,  $\mu_{\min}$  will be zero. As an example, for off-nominal input parameter set (24.0, 0.162, and 0.310), input logical sets being satisfied are: MSM, MMM, MSL, MML, LSM, LMM, LSL and LML. So, corresponding  $\mu_{\min\text{MSM}}$ ,  $\mu_{\min\text{MMM}}$ ,  $\mu_{\min\text{MSL}}$ ,  $\mu_{\min\text{MML}}$ ,  $\mu_{\min\text{LSM}}$ ,  $\mu_{\min\text{LMM}}$ ,  $\mu_{\min\text{LSL}}$ ,  $\mu_{\min\text{LML}}$  are non zero values. No other nonzero  $\mu_{\min}$  will occur. For the non zero  $\mu_{\min}$  values only, nominal P, I, D gain outputs ( $K_p$ ,  $K_i$ , and  $K_d$ , respectively) corresponding to above fuzzy sets being satisfied are taken from the Sugeno Fuzzy Rule Base Table (Table 1).
- (c) *Sugeno defuzzification* yields the defuzzified, crisp output for each gain as follows: Final crisp gain output,  $K_{\text{crisp}} = \frac{\sum_i \mu_{\min}^i K_i}{\sum_i \mu_{\min}^i}$ , where  $i$  corresponds to input logical sets being satisfied (at most 8) among 27 input logical sets,  $K_i$  is nominal  $K_{pi}$ ,  $K_{fi}$ , or  $K_{di}$ .  $K_{\text{crisp}}$  is either  $K_{p\text{crisp}}$  or  $K_{i\text{crisp}}$  or  $K_{d\text{crisp}}$ .  $\mu_{\min}^i$  is the minimum membership value corresponding to  $i$ th input logical set being satisfied.

#### 5. Input data and parameters

- (a) The constant input data (Ghoshal, 2004; Ghoshal & Goswami, 2003) of the three equal thermal generating areas are the following: governor regulation,  $R = 2.4$  Hz/pu, governor time constant,  $T_g = 0.08$  s, non-reheat time constant,  $T_t = 0.3$  s, Reheat time constant,  $T_r = 4.2$  s, Reheat parameter,  $c = 0.35$ , power system gain constant,  $K_p = 120$  Hz/pu,

**Table 1**

Two sample results for two nominal input parameter sets with optimal PID gains and transient response parameters for all optimization techniques.

Input set no.	Area nominal input parameter $T_p, t_{12}, b$	Technique	Optimal crisp PID gains			$US \times 10^3$ (-ve) (pu)	$OS \times 10^3$ (pu)	Settling time, $t_s$ (s)	Minimum figure of demerit	Optimizing time (s)
			$K_p$ (-ve)	$K_i$ (-ve)	$K_d$ (-ve)					
1.	10, 0.145, 0.125	BGA	1.6602	1.9382	1.1071	25.9	3.80	7.14	72.1277	216.80
		BGA-SA	1.9950	1.4134	0.8638	29.4	3.53	7.06	70.9481	353.2810
		RGA	2.0000	1.4408	0.9200	15.9	0.08	7.30	55.8245	145.2660
		EP	2.0000	2.0000	1.0747	25.7	3.73	7.07	70.5027	492.0310
		HEP	2.0000	1.8928	1.8213	23.6	1.91	7.83	70.5266	509.4850
		CPSO	1.9950	1.4033	0.9184	25.7	3.53	6.92	66.9522	87.9140
		HPSOIWA	1.2000	1.2000	1.2000	28.2	1.54	8.04	74.9656	186.1720
		HPSOCFA	2.0000	1.2944	0.9940	15.0	0.07	7.25	54.8174	186.0630
		HPSOCFA- Taguchi	2.0000	1.3514	0.9535	29.3	2.13	6.98	61.8422	530.1870
		EPSO	1.9834	1.9950	1.9684	20.9	2.10	7.00	57.7781	236.2300
		NPSO	2.0000	1.3686	0.9346	29.2	2.43	7.05	64.1338	200.8750
		CRPSO	2.0000	1.2963	0.9897	28.9	2.01	6.45	53.9947	195.0930
		MCASO	2.0000	1.3213	0.9341	15.5	0.08	7.15	53.5314	156.0940
		BFO	1.5097	1.9270	1.1850	14.0	1.85	7.00	54.3825	697.0630
2.	10, 0.145, 0.275	BGA	2.0000	1.5733	1.4626	12.9	0.00	7.69	60.8002	218.20
		BGA-SA	1.9702	0.6108	0.6577	17.4	0.00	7.52	59.5780	352.25
		RGA	2.0000	0.5913	0.7400	16.8	0.00	7.14	53.8020	146.89
		EP	0.9450	0.4434	0.2000	23.5	7.90	17.53	375.2334	490.10
		HEP	2.0000	0.7563	2.0000	11.1	0.24	11.5	133.5397	511.50
		CPSO	1.9950	0.6161	0.5688	18.2	1.51	8.63	80.0694	90.12
		HPSOIWA	1.2000	1.2000	1.2000	14.3	1.55	8.88	83.3018	186.00
		HPSOCFA	2.0000	0.5758	0.6770	17.3	0.00	7.47	58.7938	1860630
		HPSOCFA- Taguchi	1.9359	1.9675	1.9754	11.2	1.33	8.75	79.5858	533.1870
		EPSO	2.0000	1.9846	0.8895	15.8	1.60	7.54	61.9080	230.00
		NPSO	2.0000	0.5792	0.8848	15.6	0.00	7.76	62.6512	214.65
		CRPSO	1.9313	0.6025	0.5749	18.2	0.00	6.57	46.4773	192.30
		MCASO	1.7191	0.5369	0.5527	18.5	0.08	6.33	43.4978	152.67
		BFO	1.8946	0.5891	0.9098	15.2	0.00	7.13	53.1473	695.47

incremental load change in area1,  $\Delta P_D = 0.01$  pu. For equal areas,  $t_{p1} = t_{p2} = t_{p3} = t_p$ ;  $b_1 = b_2 = b_3 = b$ ;  $t_{12} = t_{23} = t_{31}$ .

- (b) The parameters required for the optimization techniques are the following: maximum number of iteration cycles,  $N = 200$ , Population size,  $n_p = 50$ , maximum gain ( $g_{max}$ ) = 2.0, minimum gain ( $g_{min}$ ) = 0.2. Initial gains =  $0.25 * \text{Rnd}_1$ , where  $\text{Rnd}_1$  is uniformly distributed random number in  $[0, 1]$ . Initial velocities of gains = 0.4.  $P, I, D$  gain parameters = 3, which are the variable optimization parameters. There are 27 sets of system nominal input parameters ( $t_p, t_{12}$  and  $b$ ), for each of which optimal PID Gains are to be determined by any of the optimization techniques. This is common for all optimization techniques.

For **BGA**, number of bits in a chromosome = (number of parameters)  $\times 8$ ; mutation probability = 0.004, crossover rate = 80%, selection ratio,  $s_r = 0.3$ .

For **SA**, Best initial temperature,  $C_0$  is selected as 75 °C and best  $\beta$  is selected as 0.995 after performing a lot of computer based computations.

For **EP** and **HEP** technique, strategy parameters  $\alpha$  and  $\beta$  are randomly varied between 0.1 to 0.7 for each loop by binary encoding and decoding.

For **CPSO**,  $c_1 = c_2 = 2.05$ .

For **HPSOIWA** and **HPSOCFA** techniques, constants,  $c_1 = c_2 = 2.05$ . Selection ratio,  $s_r = 0.3$ .  $w$  varies from 0.8 to 0.4 (IWA),  $CF = 0.60$  (CFA).

For **EPSO** technique,  $\text{sign} = 1.0$ ,  $w_1 = w_2 = w_3 = 0.1$ ,  $\text{tou}_1 = 0.1 * \text{Rnd}_2$ ,  $\text{tou}_2 = 0.1 * \text{Rnd}_2$ .  $\text{Rnd}_2$  is uniformly distributed random number in  $[0, 1]$ .

For **NPSO**, parameters are the same as for CPSO.

For **CRPSO**,  $C_1 = C_2 = 2.05$ , initial gains =  $0.25 * \text{rand}(1)$ , initial velocities = 0.6. The value of  $v_i^{\text{craziness}}$  may be determined by employing  $v_{\min}^{\text{craziness}} = 0.1$  and  $v_{\max}^{\text{craziness}} = 0.4$ .

For **BFO** and **MCASO**, all parameters are given in Section 3.

## 6. Computational results

Table 1 shows two computational sample sets of results out of 27 sets ( $3^3$ ) like optimal PID gains, optimal undershoots, optimal overshoots, optimal settling times, minimum values of figure of demerit corresponding to two input parameter sets for each technique, obtained by MATLAB 6.5 software run on Pentium IV of 2.4 GHz. The Table 1 is called as part of Sugeno Fuzzy Rule Base Table, which is later on used for on-line determination of off-nominal PID gains for any off-nominal input parameter set.

Figs. 2–7 show the transient response curves of  $\Delta f_1(t)$ ,  $\Delta f_{12}(t)$  and  $\Delta f_{pg1}(t)$  in p.u for any one set of nominal input parameters out of 27 sets for four techniques MCASO and BFO, respectively. Figs. 8–10 show MATLAB-SIMULINK based plots of  $\Delta f_1(t)$ ,  $\Delta f_{12}(t)$  and  $\Delta f_{pg1}(t)$  versus time for MCASO algorithm. Convergence profiles of minimum figure of demerit obtained for some techniques for a particular input parameter set are shown in Figs. 11 and 12. Table 2 shows different parameters of transient response curves of  $\Delta f_1(t)$  for one set of off-nominal input parameters using SFL. For testing the robustness, each optimizing technique is run multiple times for each input parameter set, such that finally each technique is run for a total of 200 runs. Summarized results of merit order rank-wise frequencies of occurrence of the compared optimization techniques with total 200 runs for each technique (multiple runs for each input set) are given in Table 3. Summarized overall merit order rankings of the compared optimization techniques, derived from Table 3 are shown in Table 4.

## 7. Discussions

- (i) Various aspects of optimized nominal transient response characteristics: The objective function “Figure of demerit” chosen in this work directly involves the transient response characteristics, hence it correctly determines optimum values of

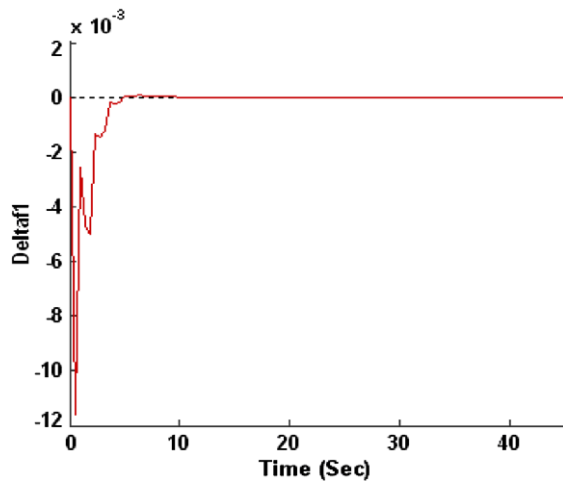


Fig. 2. Plot of Deltaf1 versus time for MCASO; nominal input parameters = (20.0, 0.545, and 0.275).

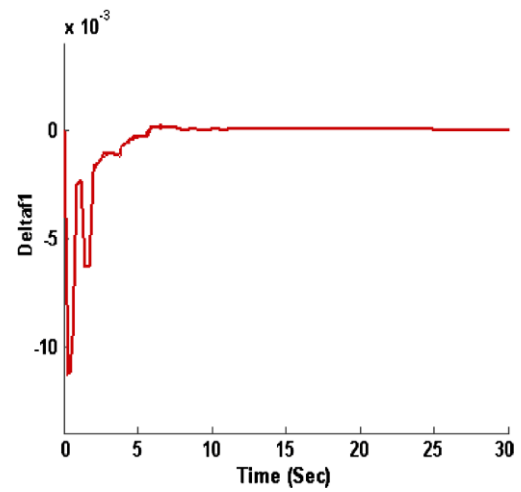


Fig. 5. Plot of Deltaf1 versus time for BFO; nominal input parameters = (20.0, 0.545, and 0.275).

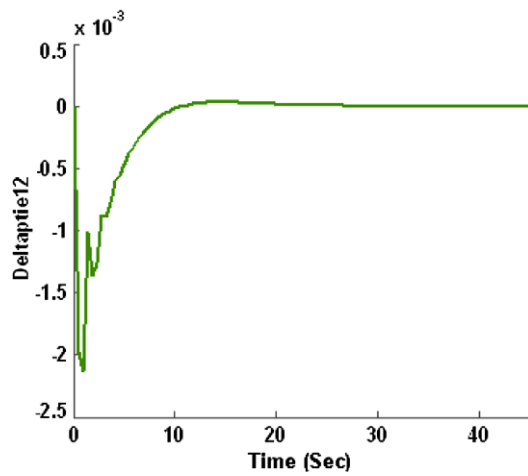


Fig. 3. Plot of Deltaptie12 versus time for MCASO; nominal input parameters = (20.0, 0.545, and 0.275).

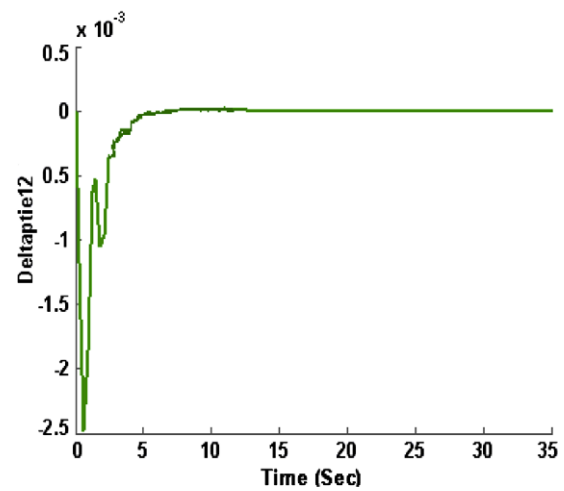


Fig. 6. Plot of Deltaptie12 versus time for BFO; nominal input parameters = (20.0, 0.545, and 0.275).

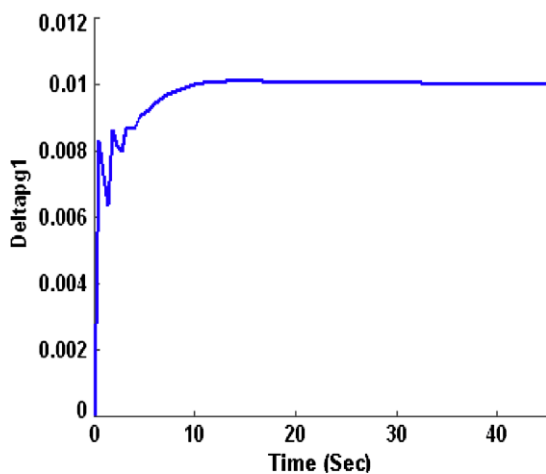


Fig. 4. Plot of Deltapg1 versus time for MCASO; nominal input parameters = (20.0, 0.545, and 0.275).

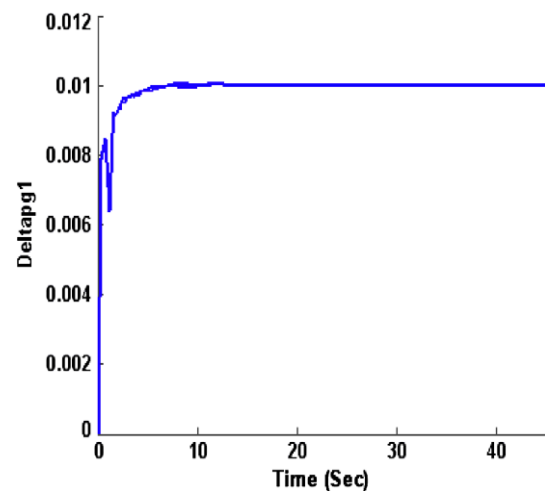


Fig. 7. Plot of Deltapg1 versus time for BFO; nominal input parameters = (20.0, 0.545, and 0.275).



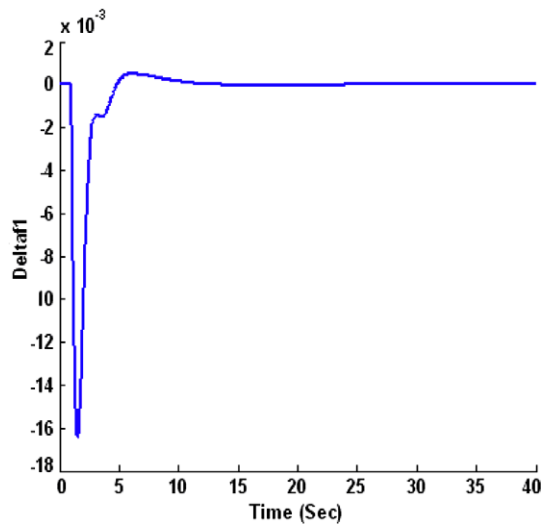


Fig. 8. MATLAB-SIMULINK based plot of Delta f1 versus time for MCASO; nominal input parameters = (20.0, 0.545, and 0.275).

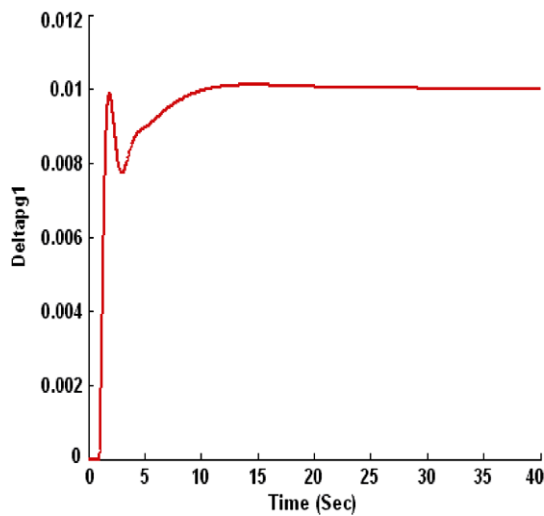


Fig. 9. MATLAB-SIMULINK based plot of Deltapg1 versus time for MCASO; nominal input parameters = (20.0, 0.545, and 0.275).

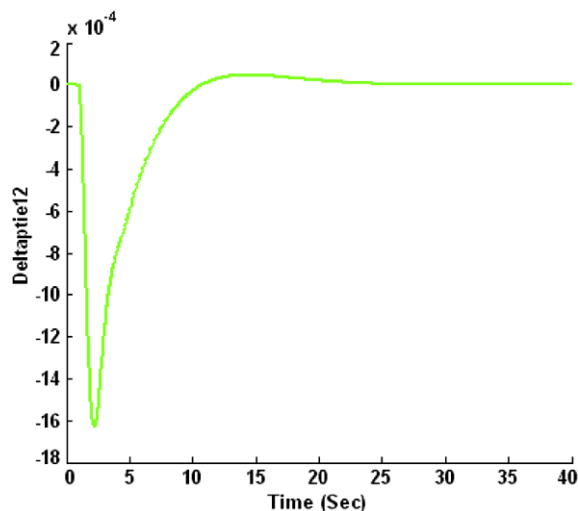


Fig. 10. MATLAB-SIMULINK based plot of Deltapie12 versus time for MCASO; nominal input parameters = (20.0, 0.545, and 0.275).

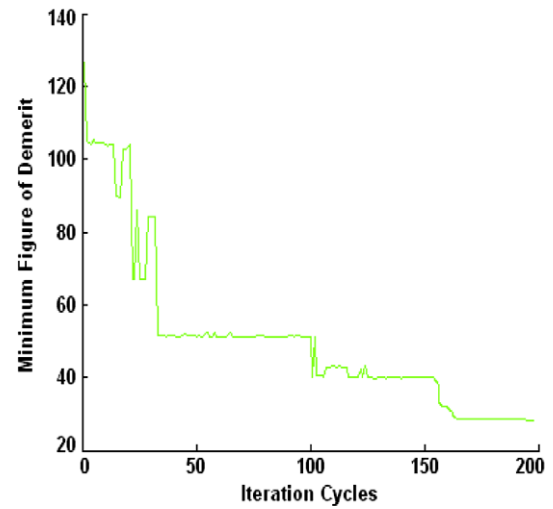


Fig. 11. Plot of minimum figure of demerit versus iteration cycles for BFO; nominal input parameters = (30, 0.345, and 0.425).

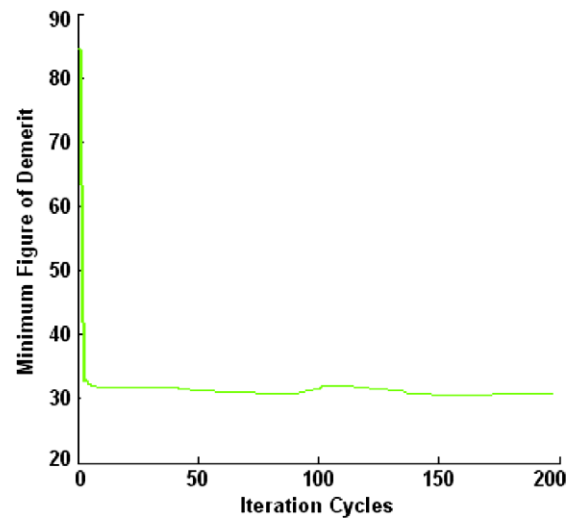


Fig. 12. Plot of minimum figure of demerit versus iteration cycles for MCASO; nominal input parameters = (30, 0.345, and 0.425).

PID gains with optimal transient response. It has also been investigated that if the weighting factor for overshoot is reduced, overshoot increases in the transient response, also resulting in other values of optimal gains. Optimal gains and transient responses are, therefore, dependent on the choice of weighting factors. Settling time because of its higher value than weighted overshoot is always imparted larger effect in reaching its minimum values. Undershoots are less affected by variations in weighting factor.

A close look into the results obtained by MCASO, BFO, CRPSO and other techniques for the input sets (20, 0.145, 0.125), (20, 0.345, 0.125), (20, 0.545, 0.125), values of minimum figure of demerit are high, and for (30, 0.145, 0.125), (30, 0.345, 0.125), (30, 0.545, 0.125), values are still higher. It means that for lower frequency bias coefficient, frequency oscillations, overshoot, settling time are more, yielding higher minimum figure of demerit. This behavior becomes more and more prominent as power system time constant increases i.e. area frequency response characteristic or damping coefficient ( $AFRC = \Delta P_D / \Delta f$ ) decreases. That is, as the effect of the change in frequency on change in load decreases, the frequency oscillations are poorly damped.

**Table 2**

SFL based on-line computation of off-nominal optimal PID gains and other transient performance characteristics for different optimization techniques.

Input set no.	Area nominal input parameter $T_p, t_{12}, b$	Technique	Optimal crisp PID gains			US $\times 10^3$ (–ve) (pu)	OS $\times 10^3$ (pu)	Settling time, $t_s$ (s)	Minimum figure of demerit	Optimizing time (s)
			$K_p$ (–ve)	$K_i$ (–ve)	$K_d$ (–ve)					
1.	24, 0.28, 0.32 (MSM, MSL, MMM, MML, LSM, LMM, LSL, LML)	GA-SA	1.9923	0.5600	1.9923	11.2	0.00	7.54	58.1060	0.1
		BGA	1.9612	0.5493	1.7842	11.7	0.00	7.82	62.5213	0.09
		RGA	1.9751	0.5907	1.3639	13.2	0.00	7.17	53.1513	0.1
		EP	2.0000	0.5661	2.0000	11.1	0.00	8.00	65.2321	0.1
		HEP	1.4728	1.7932	0.9006	15.9	1.90	7.00	55.1381	0.09
		CPSO	1.4926	0.4605	1.4580	13.1	0.00	8.23	69.4490	0.1
		HPSOIWA	1.2000	1.2100	1.2300	14.0	1.60	9.00	85.5200	0.09
		HPSOCFA	1.9950	0.6013	0.8466	16.0	0.00	7.12	53.2544	0.1
		HPSOCFA-Taguchi	1.2678	0.8964	1.3864	13.3	1.77	9.71	99.1859	0.1
		EPSO	1.9546	1.7421	1.0350	14.8	1.10	8.13	69.4973	0.1
		NPSO	2.0000	0.5643	2.0000	10.9	0.00	8.11	66.9602	0.1
		CRPSO	2.0000	0.5860	1.9892	11.1	0.00	7.00	50.2321	0.1
		MCASO	1.9999	0.6077	0.8766	15.8	0.00	6.24	41.4340	0.09
		BFO	2.0000	0.5800	2.0000	11.1	0.00	7.15	52.3546	0.1

**Table 3**

Summarized results of merit order (minimum figure of demerit values) rank-wise frequencies of occurrence of the compared optimization techniques with total 200 runs for each technique (multiple runs for each input parameter set).

Technique	Frequency of occurrence													
	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th	14th
BGA	0	0	0	0	0	22	<b>37</b>	<b>44</b>	15	22	22	15	7	16
BGA-SA	0	0	0	0	0	<b>67</b>	<b>37</b>	7	15	15	15	15	0	29
RGA	0	14	30	<b>74</b>	<b>82</b>	0	0	0	0	0	0	0	0	0
EP	0	0	0	0	0	<b>30</b>	<b>30</b>	<b>22</b>	7	7	<b>55</b>	<b>15</b>	<b>34</b>	0
HEP	0	0	0	0	0	<b>52</b>	<b>37</b>	15	22	0	22	30	15	7
CPSO	0	0	0	0	0	<b>82</b>	15	15	15	22	7	<b>37</b>	0	7
HPSOIWA	0	0	0	0	0	0	0	0	21	12	19	19	58	<b>71</b>
HPSOCFA	0	7	16	<b>82</b>	<b>88</b>	7	0	0	0	0	0	0	0	0
HPSOCFA-Taguchi	0	0	0	0	0	0	7	0	28	36	21	21	<b>59</b>	28
EPSO	0	0	0	0	0	7	0	24	<b>48</b>	<b>34</b>	19	<b>50</b>	0	18
NPSO	0	0	0	0	0	8	23	<b>38</b>	<b>53</b>	23	23	8	8	16
CRPSO	37	<b>52</b>	<b>67</b>	30	14	0	0	0	0	0	0	0	0	0
MCASO	<b>141</b>	15	<b>37</b>	0	7	0	0	0	0	0	0	0	0	0
BFO	22	<b>111</b>	<b>52</b>	15	0	0	0	0	0	0	0	0	0	0

**Table 4**

Summarized overall merit order ranking of the compared optimization techniques, derived from Table 3.

Techniques	Dominant overall rank(s)
MCASO	1st or 3rd
BFO	2nd or 3rd
CRPSO	3rd or 2nd
RGA	4th or 5th
HPSOCFA	4th or 5th
CPSO	6th, 7th to 12th
BGA-SA	6th to 14th
HEP	6th or 7th, 8th to 13th
BGA	6th to 14th
NPSO	9th or 8th, 7th to 11th
EPSO	8th to 12th
EP	11th to 13th, 6th to 8th
HPSOCFA-Taguchi	13th, 9th to 14th
PSOIWA	14th, 9th to 14th

(ii) *Sugeno Fuzzy Logic Based Response*: For on-line, off-nominal input sets of parameters, SFL is successfully applied to get on-line, optimal PID gains. SFL intelligent MCASO-PID controller performs better than any SFL intelligent PID controller based on other optimization techniques. Figs. 2–7 show the SFL based plot of Delta $f_1$ , Delta $t_{p12}$ , Delta $p_{g1}$  versus time for MCASO and BFO techniques. Table 2 shows the SFL based on-line computation of off-nominal optimal PID gains and other transient performance characteristics for different optimization techniques.

(iii) *Convergence profiles*: The minimum figures of demerit values recorded are plotted against number of iteration cycles to get the convergence profile of any technique. Figs. 11 and 12 show the convergence profiles of minimum figure of demerit of different optimization techniques. From these figures it is clear that all optimization techniques except BGA and EPSO converge well to the final sub-optimal or near optimal or true optimal values of minimum figure of demerit. But, MCASO, BFO, CRPSO and RGA converge to the optimal minimum values, whereas the rest others converge to the higher sub-optimal minimums by repeatedly revisiting the same solutions. HPSOCFA and EPSO show a few initial oscillations. BFO shows large oscillations till iteration cycles reach 100 and then reaches true minimum figure of demerit before the end of 200 iteration cycles.

(iv) *Robustness*: Inclusion of random numbers in heuristic techniques dictates to accept the performance results of these techniques upon testing the techniques for repetitive trial runs. A meaningful and acceptable conclusion may only be drawn about the optimizing techniques from the frequency of occurrence of convergence towards a predefined specific value. Two hundred independent trial runs for all the optimization techniques are individually carried out to accept the robustness of the techniques. Frequencies of occurrences of attaining various merit-order ranks and summarized overall ranks are presented in Tables 3 and 4, respectively. MCASO and BFO are the most robust techniques as their frequencies of retaining the first and second ranks, respectively, are very

consistent and high, 141 and 111 each out of 200 runs, respectively. CRPSO, RGA and HPSOCFA hold ranks from 2nd to 5th, respectively, but not so consistently. So, they are moderately good and robust. Excepting these five techniques, the rest nine techniques do not perform consistently even for sub-optimal solutions and are not robust for this specific study.

- (v) *Time of Optimization*: For the same number of iteration cycles (200), the optimization times are arranged in ascending order as follow:  $T_{CP\text{SO}} < T_{RGA} < T_{MCASO} < T_{HPSOIWA} < T_{HPSOCFA} < T_{CRPSO} < T_{NPSO} < T_{BGA} < T_{EPSO} < T_{BGA-SA} < T_{EP} < T_{HEP} < T_{HPSOCFA\_Taguchi} < T_{BFO}$ . So, inclusion of many random numbers and predefined probability of craziness is the cause of CRPSO's more execution time. Execution times of RGA and MCASO rank second and third, respectively. EP and HEP take more times of execution because of frequent population doubling and mutual competition for survival. BGA-SA takes more time due to hybridization. HPSOCFA-Taguchi takes very large time due to very rigorous Taguchi selection. The execution time of BFO is the highest because of time consuming nested loops of iteration cycles for various characteristic processes like dispersal cycle, chemotactic cycle, reproduction cycle etc.
- (vi) *Validation of the results obtained*: The PID gains obtained analytically for the best algorithms MCASO and BFO are substituted in SIMULINK diagram. Analytical transient responses obtained are validated by SIMULINK based responses (Figs. 8–10) for the same input system parameter set.

## 8. Conclusion

In this work, fourteen heuristic evolutionary search techniques have been adopted for independent determination of off-line nominal optimal PID Gains suitable for optimal transient responses in automatic generation control. BGA yields sub-optimal results. Sugeno fuzzy logic (SFL) very fast manipulates the off-line nominal optimal gains obtained from the optimizers to obtain on-line off-nominal optimal gains for any on-line varying system operating condition. MCASO based optimization yield true optimal transient response among the other optimization techniques. Hence, MCASO based optimization result yield the best transient performance characteristics.

## Appendix A

The transfer functions of different block used in the Fig. 1 are presented:

Sr. no.	Elements	Short form	Transfer function
1	Governor	Gov	$\frac{1}{1+sT_g}$
2	Turbine	Tur	$\frac{1}{1+sT_t}$
3	Reheater	Reheater	$\frac{1+c.T_r s}{1+sT_r}$
4.	Power system block	Power system	$\frac{K_p}{1+sT_p}$
5.	PID controller	PID	$K_p + K_i/s + s.K_d$

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