

A NOVEL APPROACH FOR OPTIMIZATION OF PROPORTIONAL INTEGRAL DERIVATIVE GAINS IN AUTOMATIC GENERATION CONTROL

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Abstract

Automatic Generation Control of multi-area interconnected thermal generating areas means zeroing of the integral area control error of each area, so that system frequency and tie-line changes are maintained at their scheduled values. To achieve this, in this paper, Hybrid Particle Swarm Optimization (HBPSO) / Genetic Algorithm (GA) along with Sugeno Fuzzy Logic are used to determine nominal / off-nominal optimal Proportional-Integral-Derivative gains of PID controller employed in each area. HBPSO based optimal gains result in more optimal transient responses of frequency and tie-line changes. The action of Sugeno Fuzzy logic is to adaptively manipulate the HBPSO based nominal optimal gains, resulting in off-nominal optimal gains and off-nominal optimal transient responses under on-line varying system parameters and load conditions.

1. INTRODUCTION

In a large scale power system, automatic generation control in response to area load changes and abnormal imprecise system operating parameters essentially means very fast minimization of area frequency deviations and mutual tie line power flow deviations of the areas for satisfactory and stable operation of the system. Fixed linear feedback controllers fail to provide best control performance over a wide range of off-nominal operating conditions. Optimal Matrix-Riccati based controller or state adaptive controllers involve large computational burden and time. Fast acting adaptive Sugeno fuzzy based gain controllers have been proposed using either Matrix-Riccati based optimal gains [1] and GA based optimal gains [3, 5]. In this paper it has been shown that Hybrid Particle Swarm optimized PID gains yield better transient performance than GA based gains do for all nominal and off-nominal input operating conditions for an interconnected three equal reheat thermal generating areas.

2. SYSTEM MODEL

Block diagram of closed loop controlled reheat type three-area thermal generating system [5] is shown in Fig.1. Active automatic generation control of the closed loop control system means minimizing the area control errors (ACE_i) to zero so that system frequency and tie-line power flows are maintained at their scheduled values.

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

where ACE_i is area control error of i^{th} area, b_i is frequency bias coefficient of i^{th} area, Δf_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 integral of ACE_i over a given time interval τ in Laplace domain is defined by:

$$(-M_i(s)).ACE_i(s), \quad \text{where } M_i(s) = K_p + (K_i/s) + K_D.s \quad (2)$$

and K_p , K_i and K_D 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).

Description of the system model (Fig.1) is as follows: Inputs to the PID controllers are $ACE_1(s)$, $ACE_2(s)$, $ACE_3(s)$ from top to bottom. Gain, Gain2 and Gain4 are each $b=0.425$. Gain1, Gain3 and Gain5 are each $1/R=1/2.4$. Inputs to leftmost column of summers from top to bottom are: $\{b.\Delta f_1(s), \Delta P_{tie,12}(s), \Delta P_{tie,13}(s) \text{ all } +ve\}$, $\{b.\Delta f_2(s) +ve, \Delta P_{tie,12}(s) -ve, \Delta P_{tie,23}(s) +ve\}$, $\{b.\Delta f_3(s) +ve, \Delta P_{tie,13}(s) -ve, \Delta P_{tie,23}(s) -ve\}$. Inputs to second column of summers from the extreme right and from top to bottom are: $\{\text{Step } \Delta P_D / s -ve, \Delta P_{G1} +ve, \Delta P_{tie,12}(s) \& \Delta P_{tie,13}(s) -ve\}$, $\{\Delta P_{G2} +ve, \Delta P_{tie,12}(s) +ve, \Delta P_{tie,23}(s) -ve\}$, $\{\Delta P_{G3}, \Delta P_{tie,13}(s), \Delta P_{tie,23}(s) \text{ all } +ve\}$. Transfer Fcn, Transfer Fcn3 and Transfer Fcn6 each is: $((1+s.c.T_r)/((1+s.T_g).(1+s.T_l).(1+s.T_r)))$. Transfer Fcn1,

Transfer Fcn4 and Transfer Fcn7 each is $k_p / (1+s.t_p)$. Transfer Fcn2, Transfer Fcn5 and Transfer Fcn8 each is t_{12} / s , t_{23} / s and t_{13} / s respectively, (t_{12} , t_{23} , t_{13} being equal). The values of c , T_r , T_g , T_t & R are all given in Section 6 (Input Data and Parameters). Nominal input parameters are: $t_p = 30.0$ secs, $t_{12} = 0.145$, $b = 0.425$.

The gains in the system model may be optimal nominal gains determined off-line by GA or Hybrid Particle Swarm (HBPSO) or off-nominal, on-line ones determined by fast acting Sugeno fuzzy logic with off-nominal input parameters using optimal nominal gains.

Optimization of PID gains by any of the optimization techniques corresponds to minimum undershoot (US), minimum overshoot (OS), minimum settling time (t_s) and minimum (df/dt) i.e. overall minimum figure of demerit [3, 5].

$$\text{figure of demerit} = (OS*1000)^2 + (US*100)^2 + (t_s)^2 + ((df/dt)*100)^2. \quad (3)$$

The choice of multiplying factors and the absolute determination of OS, US etc. are elaborately explained in references [3, 5].

3. GA BASED OPTIMIZATION OF PID GAINS

GA is a kind of the probabilistic heuristic search algorithm analogous to mechanics of natural selection and survival of the fittest in biology. The searching process is performed globally. A population size, n_p is chosen, containing several chromosomes. Each chromosome is a string of forty eight binary bits of which each consecutive sixteen bits represents proportional, integral and derivative gain. Evaluation of each chromosome solution string is accomplished by decoding the binary bits and calculating fitness function, which is "figure of demerit" [3, 5]. The strings with less figure of demerit will only survive for the next generation, the strings with more figure of demerit will die. The process is essentially selection and copying the elite strings in place of dying strings to regenerate the same population size. The newly generated strings now produce new off-springs by crossover and mutation. A new population is thus formed in each genetic iteration cycle. The whole iteration cycle is repeated several times till required optimal or near optimal P, I, D gain solutions are obtained for which the figure of demerit is the grand lowest.

4. HBPSO BASED OPTIMIZATION OF PID GAINS

PSO [2] is a flexible, robust population-based stochastic search/ optimization algorithm with implicit parallelism,

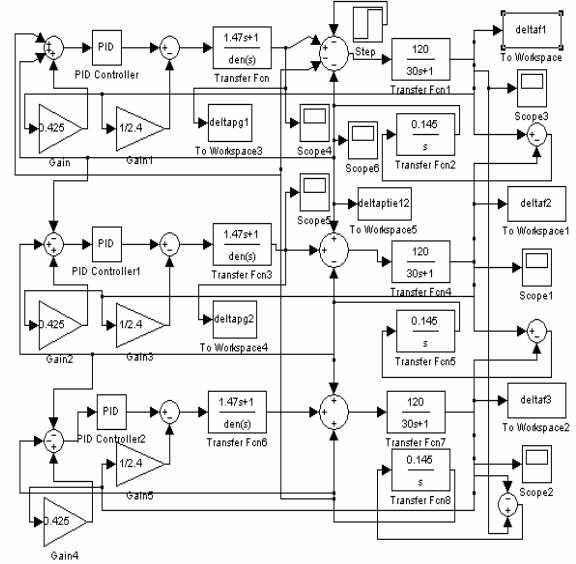


Figure-1: "MATLAB-SIMULINK" software based reheat type three-area automatic generation control block diagram (System Model).

which can easily handle with non-differential objective functions, unlike traditional optimization methods. PSO is less susceptible to getting trapped on local optima unlike GA etc.

Kennedy and Eberhart [2] developed PSO concept similar to the behavior of a swarm of birds. PSO is developed through simulation of bird flocking in multi-dimensional space. Each particle's present position is realized by the previous position and present velocity information.

Along with above classical PSO algorithm, a natural selection mechanism is also adopted [4]. The selected number of "Elite" particles with increasing order of objective value (figure of demerit) starting from its minimum is $s_r * n_p$, where s_r is selection rate and n_p is population size. The number of highly evaluated particles (lower figure of demerit) is increased while the number of lowly evaluated particles is decreased at each iteration.

After selection, the same population size is formed by copying. A linearly decreasing inertia weight from 0.92

to 0.38 is deployed as Inertia Weights Approach (IWA) [4] instead of fixed weight. Thus, the whole optimization technique differs from ordinary PSO and is denoted by HBPSO.

Steps of HBPSO algorithm [2, 4] as implemented for optimization of P, I, D gains are:

- Initialization of particles (P, I, D gains) of n_p population.
- Evaluation of figure of demerit of each particle.
- Search for Individual Minimum figure of demerit and corresponding Individual best particle.
- Search for Global Minimum figure of demerit and its corresponding Global best particle.
- (Step 5) Weight updating (Inertia Weights Approach (IWA)).
- Selection of Elite particles, Copying them over the unselected particles and Velocity updating.
- Position updating.
- Individual best position updating.
- Global best position updating.
- Iteration updating and Stopping Criteria / Repeating from Step 5.

5. BRIEF REVIEW OF SUGENO FUZZY LOGIC AS APPLIED TO GAIN SCHEDULING

Sugeno Fuzzy Logic computes off-nominal optimal gains for off-nominal on-line input parameters such as t_p , t_{12} and b .

The whole process 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.

(b) Sugeno fuzzy inference involves logical determination of logical input sets being satisfied and its corresponding nominal PID gain outputs, for given off-nominal t_p , t_{12} and b values and corresponding three membership values μ_p , μ_{t12} , μ_b and their minimum for each logical set.

(c) Sugeno defuzzification yields the defuzzified, crisp output for each gain as follows:

$$\text{Final Crisp Output, } G_{\text{crisp}} = \frac{\sum_i \mu_{\min}^{(i)} \cdot G_i}{\sum_i \mu_{\min}^{(i)}} \quad (4)$$

where i corresponds to a few satisfied logical sets

among 27 logical sets. G_i is K_{pi} , K_{li} or K_{Di} . $\mu_{\min}^{(i)}$ is the minimum membership value corresponding to i^{th} logical set.

6. INPUT DATA AND PARAMETERS

i) The constant input data [3, 5] of the three equal thermal generating areas are the following: Governor regulation, $R = 2.4$ Hz/p.u., 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/p.u., Incremental load change in area1, $\Delta P_D = 0.01$ p.u.

ii) The parameters required for the optimization algorithms are the following: For GA, Crossover rate = 100%, Mutation probability = 0.004, mutation precedes crossover. For HBPSO algorithm, Maximum gain (g_{\max}) = 2.0, Minimum gain (g_{\min}) = 0.2. Initial gains = $0.25 \cdot \text{Rnd}_1$, where Rnd_1 is uniformly distributed random number in [0,1]. Initial velocities of gains = 0.4, $w_{\max} = 0.9$, $w_{\min} = 0.2$, constants, $c_1 = c_2 = 2.05$ [4], Selection ratio, $s_r = 0.3$. Maximum number of iteration cycles, $N = 100$, Population size, $n_p = 50$.

7. COMPUTATIONAL RESULTS

Table I shows some computational results out of 27 results obtained by MATLAB 6.1 software run on Pentium IV of 2.4 GHz. GA based optimal Integral gains and Transient Response Parameters have been adopted from reference [3]. Fig.2 and Fig.3 show the transient response curve of $\Delta f_i(t)$ for nominal parameters (10, 0.345, 0.425) (input data set 1) and (30, 0.345, 0.275) (input data set 2) respectively. For input data set 1, transient responses are verified by “MATLAB-SIMULINK” software and shown in Fig.5 and Fig.6.

8. DISCUSSIONS ON THE RESULTS

i) Optimal PID control is much better than optimal integral control as shown in Fig.2 and Fig.3. Integral control always yields much higher undershoot, overshoot, settling time and very large overshoot oscillations before settling down. PID control damps the oscillations very fast with very large reduction of all transient response parameters.

ii) It is clear from the figure of demerit column of Table I and Fig.2, Fig.3 and Fig.4 that HBPSO yields the true optimal performance. As compared with GA based results, HBPSO based area1 frequency deviation, $\Delta f_i(t)$, areal generation deviation, $\Delta P_{G1}(t)$ and mutual tie line

power flow deviation, $\Delta P_{tie,12}(t)$ have lesser undershoots, overshoots and settling time, resulting in lesser values of figure of demerit. GA fails to give optimal performance. So, it proves that GA has disadvantages of poor

convergence near global optimum and premature convergence to suboptimal, local solution. Thus, HBPSO proves to be an effective tool for optimization of P, I & D gains.

Table I

Nominal Input Parameter Sets Versus Optimal Integral Gains [3], Optimal PID Gains and Transient Response Parameters. Input data sets 1, 2 & 3 are (10.0, 0.345, 0.425), (20.0, 0.145, 0.275) and (30.0, 0.345, 0.275) respectively.

Nominal Input Parameters			Algorithm	Optimal PID / Integral (Intgl) Gains			Transient Response Parameters					Fig. of de-Merit (Fdm)	Exe. Time (sec)
t_p	t_{12}	b		Prop. Gain K_p	Intgl. Gain K_i	Deriv. Gain K_d	Opt Cyc.	US $\times 10^3$ (-ve) (pu)	OS $\times 10^3$ (pu)	t_s (sec)	$(df/dt) \times 10^3$ (Hz/sec)		
10.0	0.345	0.425	GA(PID)	1.49	1.77	1.23	30	14.8	2.1	8.6	15.9	83.1	132
			GA(Intgl)	-	0.14	-	57	35.5	4.0	31.0	71.0	1040	125
			HBPSO (PID)	1.99	0.64	0.86	98	12.3	0.1	4.8	18.6	28.0	127
20.0	0.145	0.275	GA(PID)	1.98	1.72	1.04	32	17.2	3.3	6.9	34.4	73.3	133
			GA(Intgl)	-	0.33	-	59	32.5	9.8	23.5	51.7	686	128
			HBPSO (PID)	1.99	0.57	1.30	80	16.1	0.1	5.0	32.2	38.0	124
30.0	0.345	0.275	GA(PID)	1.98	0.65	1.11	60	12.0	0.4	7.3	24.1	60.7	133
			GA(Intgl)	-	0.19	-	25	20.1	4.3	34.5	33.8	1225	124
			HBPSO (PID)	1.99	0.62	1.67	73	10.6	0.1	5.0	21.1	30.6	125

iii) HBPSO algorithm determines the optimal gains in lesser times ranging from 125.1 sec to 126.6 sec, whereas GA takes around 132.0 sec (Table I). So, HBPSO algorithm proves to be a faster optimizing tool.

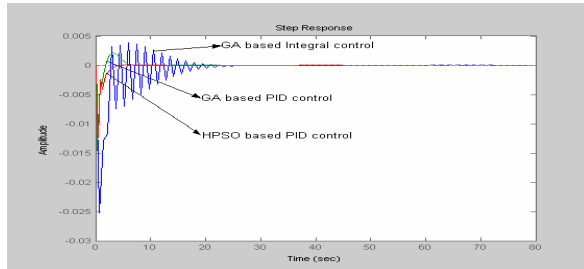


Fig.2. Computed Transient Response Plot of Frequency Error, $\Delta f_1(t)$ (deltaf1(t)) for GA and HBPSO (HPSO) with input data set 1.

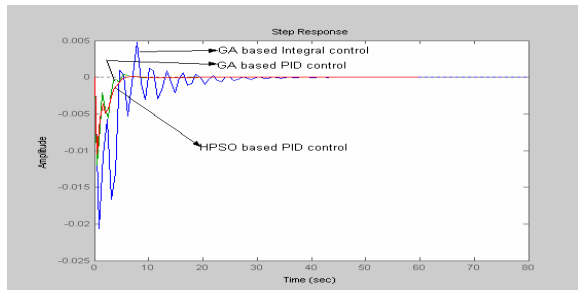


Fig.3. Computed Transient Response Plot of Frequency Error, $\Delta f_1(t)$ (deltaf1(t)) for GA and HBPSO (HPSO) with input data set 3.

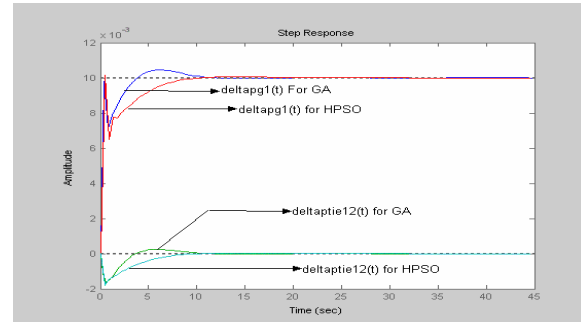


Fig.4. Computed Transient Response Plot of Generation Error, $\Delta P_{G1}(t)$ (deltapg1(t)) and $\Delta P_{tie,12}(t)$ (deltaptie12(t)) for GA and HBPSO (HPSO) with input data set 1.

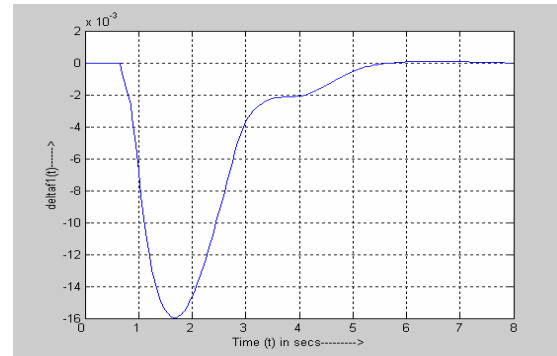


Fig.5. MATLAB-SIMULINK based Transient Response Plot of Frequency Error, $\Delta f_1(t)$ (deltaf1(t)) for GA with input data set 1.

iv) Large values of t_p around 10, 20 or 30 secs., low values of b around 0.125 and low values of t_{12} around 0.145 or 0.345 or 0.545 yield large undershoots, overshoots, settling times (Fig.2) and hence high values of figure of demerit. These values again become lower and lower as b increases from 0.125 to 0.425. For input values (10, 0.545, 0.125) high frequency oscillations occur in the first undershoot and first overshoot. For input values (20, 0.545, 0.125) less undershoot oscillations occur, overshoot oscillations are damped. For input values (30, 0.545, 0.125), two high equal undershoots occur (Fig.3). Undershoot oscillations become more and more damped as b increases.

v) The initial, sharp undershoot kicks of $\Delta f_1(t)$ are large, lying between -0.010 Hz. and -0.036 Hz.. The (df/dt) values are also large, lying between 0.015 Hz./sec and 0.075 Hz./sec whereas the overshoots and settling times are minimized to a greater extent. The reason lies in the choice of weighting factors in the formulation of “figure of demerit” objective function. Overshoots are associated with multiplying factor as 1000, whereas undershoots and (df/dt) values with 100. High settling times do not require any amplification. As compared with GA based integral / PID control, HBPSO minimizes more all the transient response parameters (Table I).

vi) The nominal gains computed by HBPSO in the present work are true optimum, resulting in optimal transient responses. Sugeno fuzzy logic extrapolates optimal nominal gains to determine off-nominal gains and corresponding off-nominal transient responses for off-nominal input parameters. The off-nominal performance evaluated by Sugeno fuzzy logic has been tested and proved to be equally effective for various on-line, off-nominal parameters [3, 5].

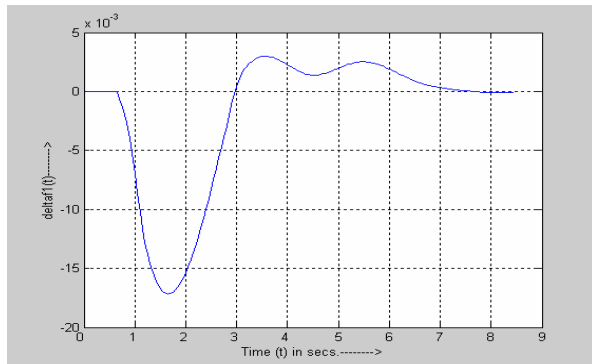


Fig.6. MATLAB-SIMULINK based Transient Response Plot of Frequency Error, $\Delta f_1(t)$ ($\Delta f_1(t)$) for HBPSO with input data set 1.

9. CONCLUSION

A novel heuristic search technique, Hybrid Particle Swarm Optimization (HBPSO) becomes a faster and more effective optimizing tool for true optimization of PID gains for nominal system input parameters in automatic generation control. It is observed that unlike GA, HBPSO does not get trapped at sub-optimal local solutions.

Optimal PID control yields much better transient responses than Optimal Integral control.

Sugeno fuzzy logic technique is very simple to implement and very fast acting. It utilizes the nominal off-line optimal gains as computed by optimization algorithm in on-line, adaptive gain scheduling for varying on-line off-nominal system parameters.

10. REFERENCES

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