International Journal of Computer Theory and Engineering, Vol. 2, No. 2 April, 2010
1793-8201

Application of GA and PSO Tuned Fuzzy Controller for AGC of Three Area Thermal-Thermal-Hydro Power System

S. K. Sinha, R. N. Patel, *Member, IEEE,* and R. Prasad, *Member, SSI*

***Abstract*—In this work applications of Genetic Algorithm and Particle Swarm Optimization techniques have been used to improve the performance of the Automatic Generation Control (AGC) in a three area power system. Genetic Algorithm and Particle Swarm Optimization have been used for optimizing the parameters of a Fuzzy logic controller (acting as the secondary controller in the AGC system).The controllers give improved dynamic performances for three area thermal-thermal-hydro power system under a variety of operating conditions.**

***Index Terms*—Automatic generation control, Frequency deviation, Fuzzy logic, Genetic algorithm, Particle swarm optimization, Tie line power deviation.**

I. Introduction

In order to ensure constancy in frequency and tie line power of an interconnected multi-area power system it is necessary to design a suitable Automatic Generation Control (AGC) system which maintains the load and generation balance in each area. With change in load, the operating point of a power system changes, and hence, the system may experience deviations from nominal system frequency and scheduled power exchanges to other areas. AGC tries to achieve this balance by maintaining the system frequency and the tie line flows at their scheduled values. The AGC action is guided by the Area Control Error (ACE), which is a function of system frequency and tie line flows. The ACE represents a mismatch between area load and generation taking into account any interchange agreement with the neighboring areas [1], [2]. In the load frequency control problem, frequency and tie-line power should be kept as near scheduled value as possible, which is difficult to achieve due to fluctuating nature of the load.

The operating point of the power system changes in a daily cycle due to the inherent nature of the changing load. This poses the difficulty in optimizing the conventional controller gains. Thus, it may fail to provide the best dynamic response. The non-linear and complex structure of electric power systems and fast changes in frequency with change in load has necessitated the use of intelligent systems that combine knowledge, techniques and methodologies from various sources for the real-time control of power systems [1]-[7]. In practice different conventional control strategies are being used for AGC. Yet, the limitations of conventional PI and PID controllers are: larger response time, lack of efficiency and poor handling of system nonlinearities. Artificial Intelligence techniques like Fuzzy Logic, Artificial Neural Networks, Genetic Algorithms and Particle Swarm Optimization can be applied for automatic generation control, which can overcome the limitations of conventional control methods [8]-[10]

Manuscript received July 20, 2009. This work was supported by AICTE, New Delhi (INDIA) through the 'Career Award for Young Teachers' (AICTE File No. 1-51/FD/CA/07/2007-08) to Dr. R. N. Patel.

S. K. Sinha is with the Department of Electrical Engineering, College of Engineering Roorkee, Roorkee, India (phone: 91-9411152876; fax: 91-1332-270307; e-mail: sinha.sanjay66@gmail.com).

R. N. Patel is with the dept. of Electrical Engineering, SSCET, Bhilai (C.G.), India (Corresponding Author: phone: +91-788-6458901; fax: 91-788-2291606; e-mail: ramnpatel@gmail.com).

R. Prasad is Professor in the Department of Electrical Engineering at IIT Roorkee, Roorkee, India (e-mail: rpdeefee@iitr.ernet.in).

II. Application Of Combined Intelligence Techniques

The genetic algorithm (GA) and particle swarm optimization (PSO) are the two very effective methods for problems related to optimization of non-linear objective functions [11]-[13]. Both of these algorithms search from many points in the search space at once and yet continually narrow the focus of the search to the areas of the observed best performance. These algorithms can be applied to solve a variety of optimization problems that are not well-suited for standard optimization algorithms, including problems in which the objective function is discontinuous, non-differentiable, stochastic, or highly nonlinear [13].

The genetic algorithm is a global search technique for solving optimization problems, which is essentially based on the theory of natural selection, the process that drives biological evolution. In all optimization problems, there is a problem of maximizing or minimizing an objective functions f(x) for a given space x of arbitrary dimension. A brute force which would consist in examining every possible x in order to determine the element for which f(x) is optimal is clearly infeasible. GA gives a heuristic way of searching the input space for optimal x, that approximates brute force without enumerating all the elements and therefore bypass performance issues specific to exhaustive search. The flowchart in Fig.1 explains the process in brief.

Particle swarm optimization is a population based stochastic optimization technique, inspired by social behavior of bird flocking or fish schooling. The system is initialized with a population of random solutions and searches for optima by updating generations. In PSO, the potential solutions, called particles, fly through the problem

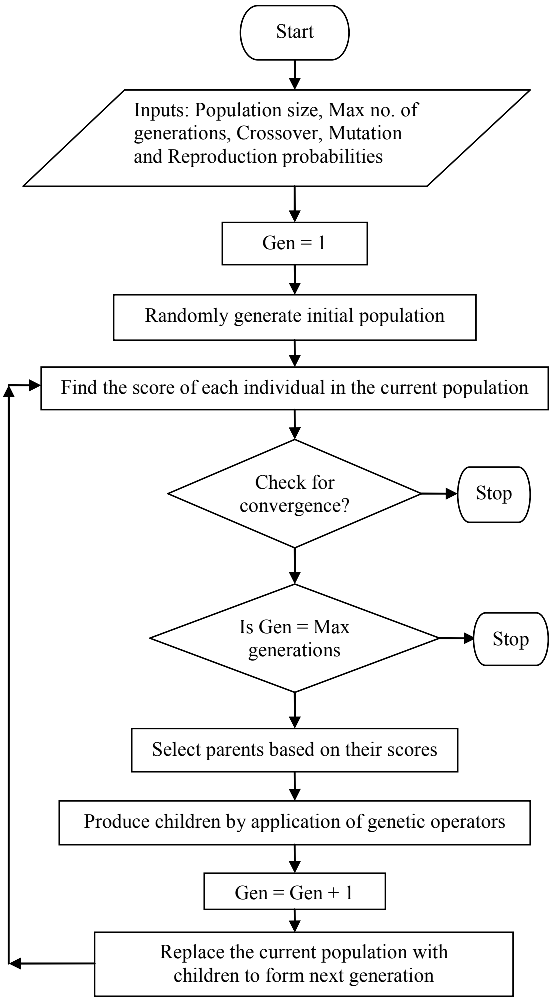

Fig. 1. Optimization process with GA

space by following the current optimum particles. In PSO technique, each individual adjusts its flying according to its own flying experience and its companion's flying experience. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. This value is called 'pbest'. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called 'gbest'. The flowchart given in Fig. 2 explains the process briefly. The following equations give the present velocity and position vectors:

$$V_i^{k+1} = wV_i^k + c_1\, rand_1()*(pbest_i - s_i^k) + c_2\, rand_2()*(gbest - s_i^k) \quad (1)$$

$$w = wMax-[(wMax-wMin* iter]/maxIter \quad (2)$$

$$s_i^{k+1} = s_i^k + V_i^{k+1} \quad (3)$$

where,
v_i^k = velocity of particle i at iteration k,
w = weighting function,
c_j = learning factor, usually c1 = c2 = 2
rand = random number between 0 and 1,
s_i^k = current position of particle i at iteration k,
$pbest_i$ = pbest of particle i,

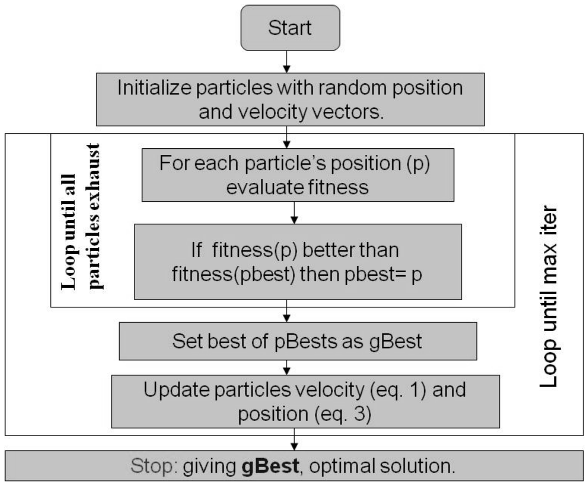

Fig. 2. flow chart of particle swarm optimization

gbest = gbest of the group,
wMax= initial weight,
wMin = final weight,
maxIter = maximum iteration number, and
iter = current iteration number.

Artificial Intelligence techniques like Fuzzy logic, GA and PSO have been used to improve the performance of the Automatic Generation Control system [13]. Instead of applying GA and PSO independently for optimizing the parameters of the AGC system with a Fuzzy Logic controller (acting as the secondary controller in the AGC system), we can use these techniques in combination (e.g. PSO tuned Fuzzy controller or GA tuned Fuzzy controller) to tap in the advantages of both the Artificial Intelligence techniques, namely Fuzzy and GA/PSO [12]. The main objectives of the work thus are:

1) To consider interconnected thermal-thermal-hydro system in which the Fuzzy Logic Controller (FLC) is used.
2) To examine tunable parameters of the FLC in order to get optimal dynamic response of the systems considered above.
3) To optimize the tunable parameters with GA and PSO.
4) To evaluate the dynamic responses of the system with optimized FLC considering load disturbances in one or more areas and to compare them with those obtained with the Fuzzy controllers.

III. Intelligent Tuning Of Fuzzy Logic Controller

Fuzzy Logic Controller (FLC) can be described by five different functional blocks, namely fuzzification, rule-base, data-base, inference engine, and de-fuzzification [14]. Since the inputs and the outputs of a fuzzy controller must be real numbers in order to match the sensors' and the actuators' requirements, fuzzification of input variables and de-fuzzification of output variables are necessary. The purpose of fuzzification is to transform the real sensor data into fuzzy linguistic terms so that further fuzzy inferences can be performed according to the rule-base. Commonly used set of fuzzy terms are shown in Fig. 3.

In order to simplify the notation, the fuzzy linguistic terms in the premise of the rules in the rule-base are sometimes defined within the range of [0, 1]. As a result, it is necessary to normalize the actual variations of the sensor inputs into the interval of [0, 1]. The input scaling factors, G^{E} and G^{CE}, are determined by the experts or designers so that the universe of discourse of the input variables are mapped into the unity interval, as shown in Fig. 4.

It can be easily seen that an input scaling factor of G^{1} and a normalized set of linguistic terms are equivalent to a set of linguistic terms with the universe of discourse between $\left[-\frac{1}{G_1}, \frac{1}{G_1}\right]$. Now, the scaling factors G^{E} and G^{CE} are altered during the tuning process and become G_E^1 and G_{CE}^1 such that:

$$G_E^1 = K_E \times G^E \tag{4}$$

and

$$G_{CE}^1 = K_{CE} \times G^{CE} \tag{5}$$

Where, K_E and K_{CE} the scaling factors.

Therefore, the fuzzy controller can be represented as shown in the Fig. 5, where E and CE indicate the error and change in error inputs. The error input is obtained by comparing the present speed (/output) with the reference value as shown in figure. The input scaling factors are the coefficients between the universe of discourse of the input variables and the unity interval, in which are supposedly constant if the range of input variations are approximately known. For an auto-tuning or learning controller design, most of the parameters are not known and the tuning of a set of parameters according to a learning scheme, such as the genetic algorithm, may be able to improve the system performance and thus derive a better controller.

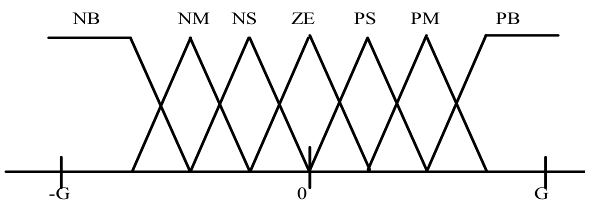

Fig. 3. membership functions of fuzzy terms

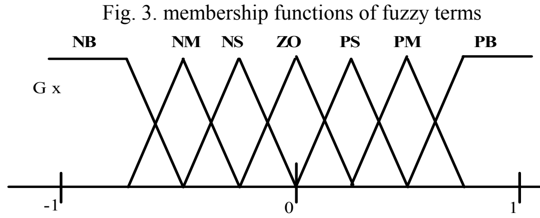

Fig. 4. normalized linguistic terms

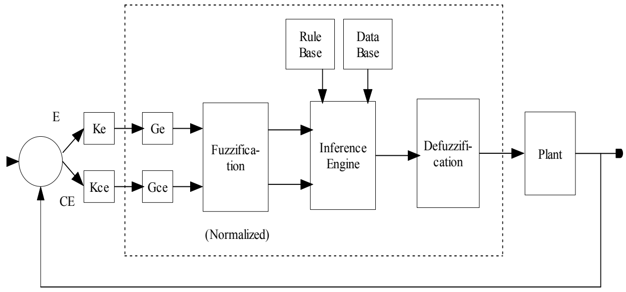

Fig. 5. tuning parameters for input scaling factors

IV. System Investigated And results

Investigations have been carried out on a three area interconnected thermal-thermal-hydro power system. Simulation model has been developed using MATLAB as shown in Fig. 6. Fig. 7 shows the fuzzy controller contained within Subsystem1, 2 and 3 of the model in Fig. 6. The system has been simulated for step load perturbation separately using the following controllers:

- Fuzzy logic controller
- GA tuned FL controller and
- PSO tuned FL controller

The fuzzy logic, an extension of classical set theory, offers the advantage of implementing the control strategy in qualitative and symbolic form. An example of a fuzzy rule in this system is: if the ACE is positive but is returning to zero at a slow rate, don't do anything. This is very difficult to implement in a mathematical formula because 'slow' is not an exact number but a qualitative expression.

The ACE is main component required for regulation of AGC [13]. ACE and $AC\dot{E}$ (which is derivative of ACE in discrete mode) have been chosen as inputs to FLC. Various number of triangular Membership Functions (MF) such as 3, 5, 7 have been used to study their impact on system dynamic performance. The input variables to the Fuzzy Controller are ACE and $AC\dot{E}$ (also referred in the paper as del_ACE) respectively. Table I shows the rule base for three membership functions, which gives the best result for the present problem. Defuzzification to obtain crisp value of FL controller output is done by centre of maximum method [14]. Table II and Table III show the optimized values of scaling factors for fuzzy controller using GA and PSO respectively, where the variables X and Y indicate the optimized values of the two scaling factors.

TABLE I. Rule Base for 3 Membership Functions

(del_ACE→) **(ACE↓)**	**NL**	**ZE**	**PL**
NL	NL	NL	ZE
ZE	NL	ZE	PL
PL	ZE	PL	PL

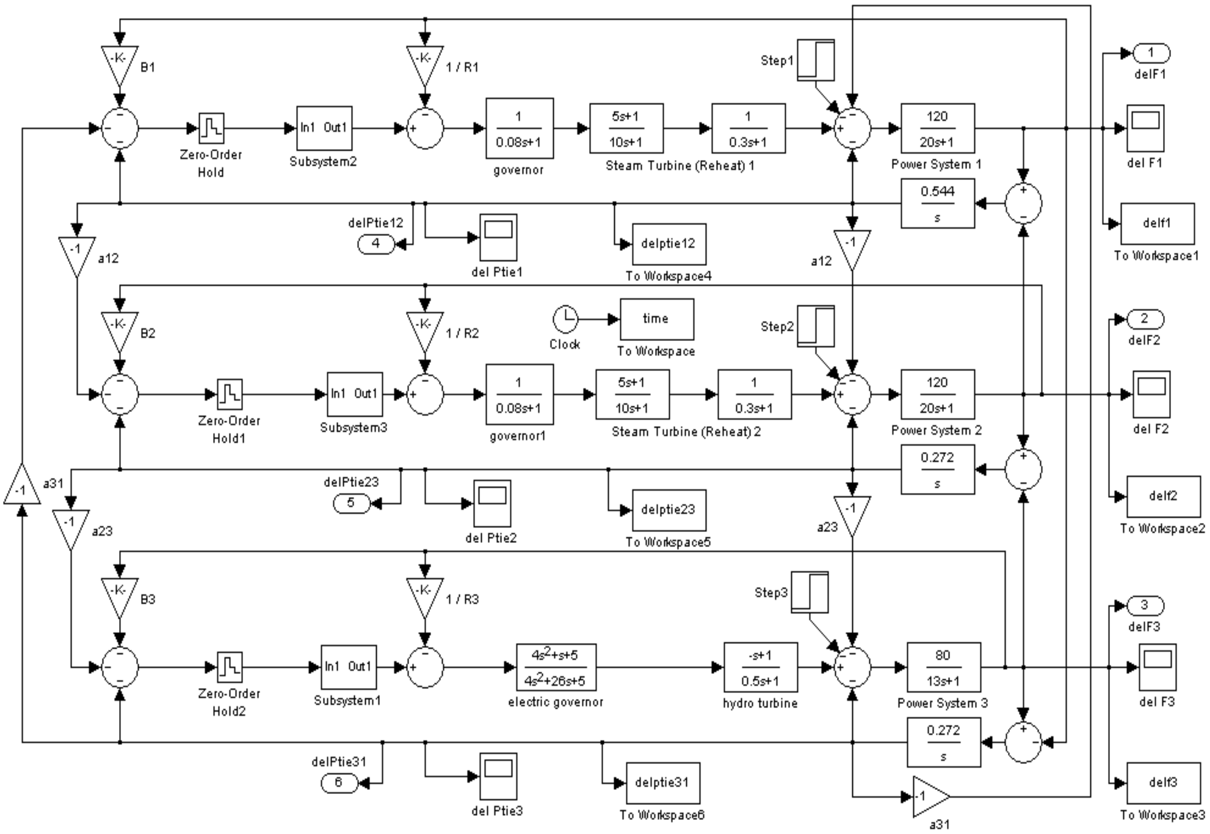

Fig. 6. Block Diagram of Three Area Thermal- Thermal-Hydro System

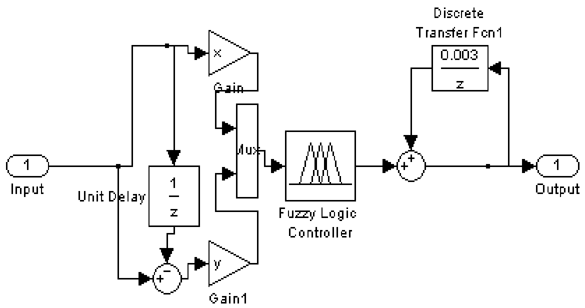

Fig. 7. Fuzzy controller within the subsystems

TABLE II. OPTIMIZED VALUES OF SCALING FACTORS USING GA

	1% SLP in Area	X	Y
Controller Parameters Optimized by GA	First Thermal Area	9.575	7.499
	Second Thermal Area	9.889	9.469
	Hydro Area	6.323	9.158

TABLE III. OPTIMIZED VALUES OF SCALING FACTORS USING PSO

	1% SLP in Area	X	Y
Controller Parameters Optimized by PSO	First Thermal Area	3.804	1.579
	Second Thermal Area	3.802	4.355
	Hydro Area	5.066	4.731

Fig. 8 to Fig. 12 show the response for 1% SLP (step load perturbation) in first thermal area, Figs.13 to 16 show the response for 1% SLP in second thermal area whereas Fig. 17 to Fig. 21 show the response for 1% SLP in hydro area.

Figs. 8 to 21 show comparison of dynamic responses between modified FLC, PSO tuned FLC and GA tuned FLC considering 1% step load perturbation in thermal area as well as in the hydro area, with R=2.4 in thermal area and 4.8 in hydro area. In all these plots the legend with subscript 'ga' indicates the result with GA tuned FLC, similarly subscript 'pso' indicates result with PSO tuned FLC and the third plot indicates normal FLC. The dynamic performance of a GA tuned as well as PSO tuned Fuzzy controller are better than a simple fuzzy controller in terms of ensuring a zero steady-state error in frequency and tie line power flow deviation because the parameters (namely the scaling factors of Fuzzy Controller) are tuned by artificial intelligence techniques. It was observed that the two tuning algorithms namely, PSO and GA give almost similar performance. In most of the cases, the performance of GA tuned FLC is slightly better than the PSO tuned FLC in terms of oscillations in frequency and tie power flow, although the final steady state values are the same. Presence of FLC in all three areas gives zero steady state error; but GA and PSO tuned FLC provide less peak overshoot and the settling time is also less irrespective of the location of the perturbation in either one area or in more than one areas.

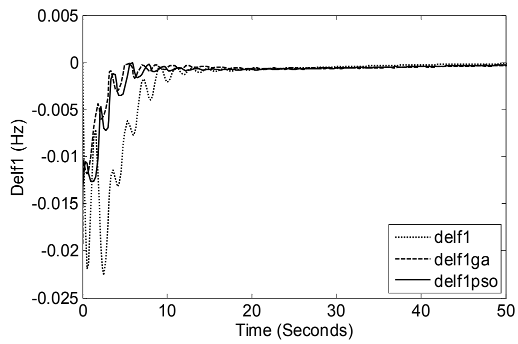

Fig. 8. Change in frequency of Area 1

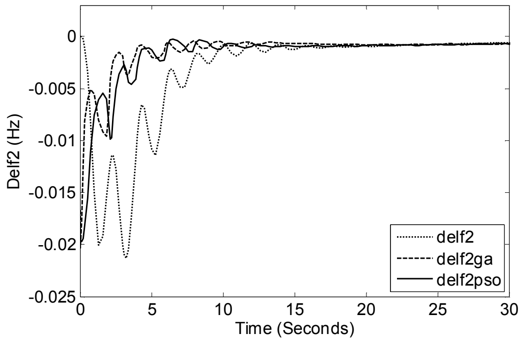

Fig. 9. Change in frequency of Area 2

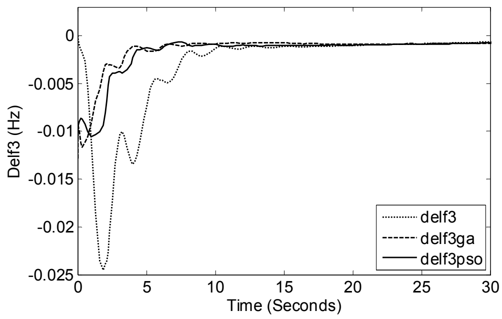

Fig. 10. Change in frequency of Area 3

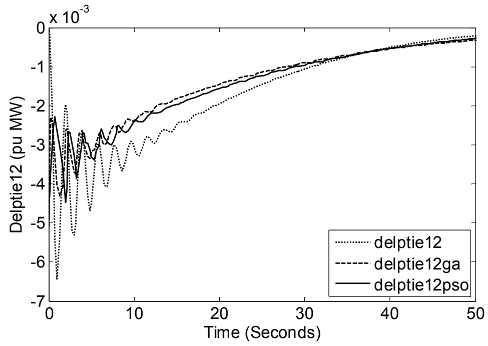

Fig. 11. Change in Tie Line Power ptie12

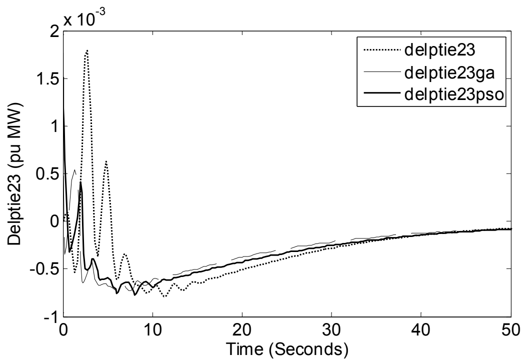

Fig. 12. Change in Tie Line Power ptie23

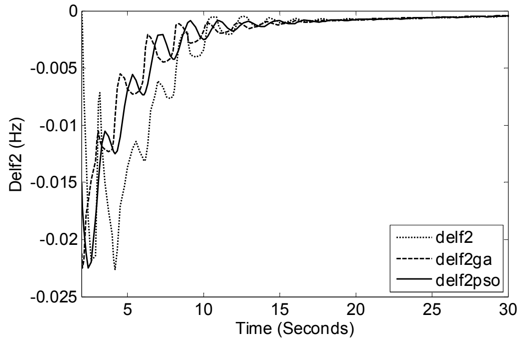

Fig. 13. Change in frequency of Area 2

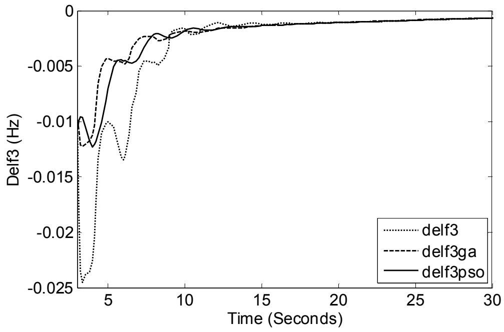

Fig. 14. Change in frequency of Area 3

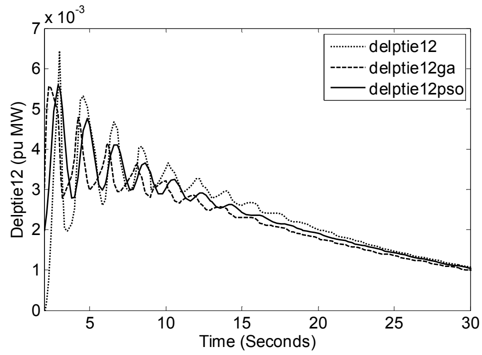

Fig. 15. Change in Tie Line Power ptie12

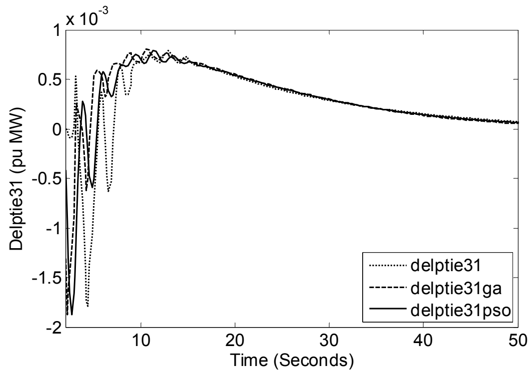

Fig. 16. Change in Tie Line Power ptie31

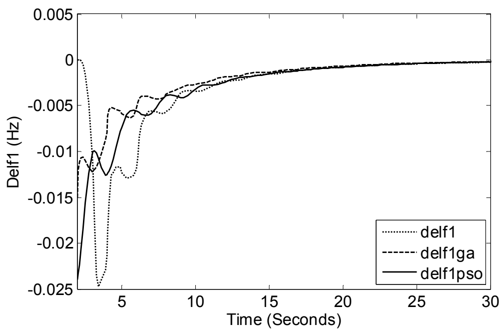

Fig. 17. Change in frequency of Area 1

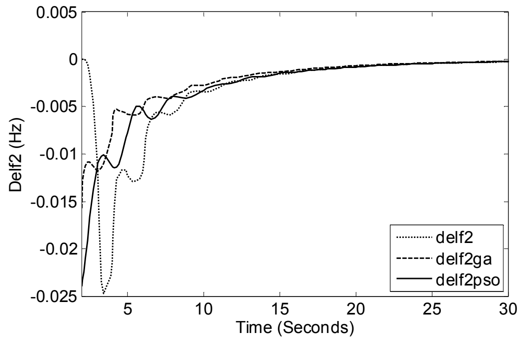

Fig. 18. Change in frequency of Area 2

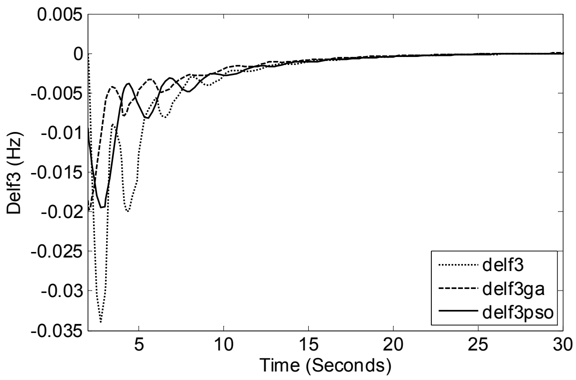

Fig. 19. Change in frequency of Area 3

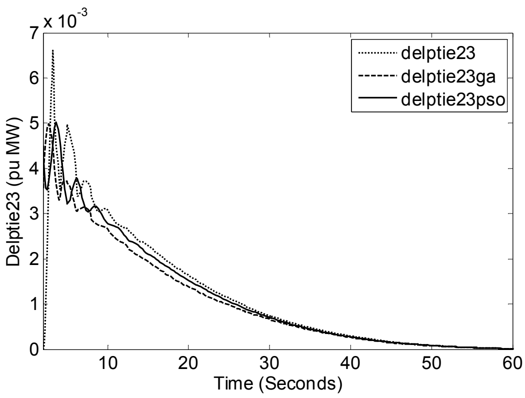

Fig. 20. Change in Tie Line Power ptie23

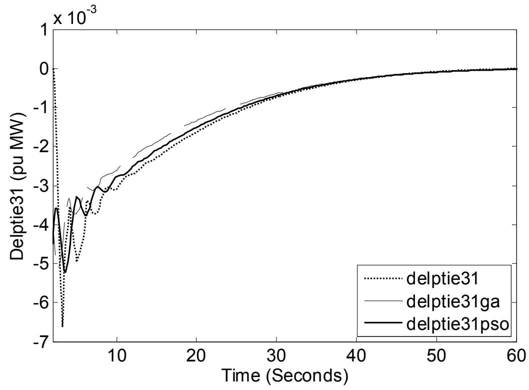

Fig. 21. Change in Tie Line Power ptie31

V. CONCLUSIONS

The optimized controllers, namely PSO tuned FLC and GA tuned FLC controllers, have been tried out for AGC of a three area thermal-thermal-hydro system. Analyses of these responses clearly reveal that GA tuned FLC and PSO tuned FLC provide better dynamic responses compared to the FLC. Presence of FLC in all the areas guarantees zero steady state error; but GA tuned and PSO tuned FLCs provide less peak overshoot and the settling time is also less irrespective of the location of the perturbation in any area. The effect of tunable parameters of Fuzzy controllers was studied in detail and the combined intelligence techniques were used for parameter tuning. It was also observed that in most of the cases, the performance of GA tuned controller is slightly better than the PSO tuned FLC in terms of oscillations in frequency and tie power flows. The values of tuned parameters (i.e. scaling factors in Fuzzy controller) are also different in the two techniques. The performances the intelligent controllers are far better as compared to the conventional PI controllers and they are also robust to the variation in system parameters and nature of disturbance.

APPENDIX: NOMINAL PARAMETERS OF THERMAL – THERMAL- HYDRO SYSTEM INVESTIGATED

f = 60 Hz	$D_1 = D_2 = 8.33*10^{-3}$ p.u. MW/ Hz
T_g = 0.08 sec	$R_1 = R_2$ = 2.4 Hz/p.u. MW R_3 = 4.8 Hz/p.u. MW
T_r = 10.0 sec	T_t = 0.3 sec
$H_1 = H_2 = H_3$ = 5 sec	K_p = 1.0
$P_{r1} = P_{r2} = P_{r3}$ =2000 MW	K_d = 4.0
$P_{tie,\ max}$ = 200 MW	K_i = 5.0
K_r = 0.5	T_w = 1.0 sec

REFERENCES

[1] D.M.V. Kumar, "Intelligent controllers for automatic generation control," Proceedings of IEEE TENCON'98, Energy, Computer, Communication control, vol. 2, 1998, pp. 557-574.
[2] Y. L. Abdel-Magid and M M. Dawoud, "Tuning of AGC of interconnected reheat thermal systems with genetic algorithms," IEEE International Conference on Systems, Man and Cybernetics, Vancouver, BC, vol. 3, 1995, pp. 2622 – 2627.
[3] R. N. Patel, S. K. Sinha, and R. Prasad, "Design of a Robust Controller for AGC with Combined Intelligence Techniques", International Journal of Electrical Power and Energy Systems Engineering, vol. 1, no. 2, pp. 95-101, Spring 2008.

[4] K. De Jong, "Adaptive system design: a genetic approach," IEEE Trans. Systems, Man and Cybernetics, SMC-10, no. 9, pp. 1566-574, Sept. 1980.
[5] P. J. Fleming and C. M. Fonseca, "Genetic algorithms in control systems engineering," Research Report No. 470, Dept. of Automatic control and Systems Engineering, University of Shefleld, Sheffield, U.K., March 1993.
[6] R. C. Eberhart and Y. Shi, "Particle swarm optimization: developments, applications and resources," Proceedings of the IEEE Congress on Evolutionav Computation (CEC 2001), Seoul, Korea, 2001, pp. 81-86.
[7] S. Panda and R. N. Patel, "Optimal Location of Shunt FACTS Controllers for Transient Stability Improvement Employing Genetic Algorithm", Electric Power Components and Systems, vol. 35, no. 2, pp. 189-203, Feb. 2007.
[8] Y. L. Abdel-Magid and M. A. Abido, "AGC tuning of interconnected reheat thermal systems with particle swarm optimization," Proc.10th IEEE International Conference on Electronics, Circuits and Systems, ICECS, vol. 1, 2003, pp. 376- 379.
[9] S. P. Ghoshal, "Application of GA/GA-SA based fuzzy automatic generation control of a multi-area thermal generating system," Electric Power Systems Research, vol. 70, no. 2, pp. 115-127, July 2004.
[10] G. A. Chown, R. C. Hartman, "Design & experience of fuzzy logic controller for automatic generation control (AGC)," IEEE Trans. on Power Systems, vol. 13, no. 3, pp. 965-970, Aug. 1998.
[11] A.A.A. Osim and A.R. Aoki, "Particle swarm optimization for fuzzy membership functions optimization," Proc. 2002 IEEE International Conference on Systems, Man and Cybernetics, vol. 3, Oct. 2002, pp. 6-10.
[12] Y.L. Karnavas and D.P. Papadoppulos, "AGC for autonomous power system using combined intelligent techniques," Electric Power Systems Research, vol. 62, no. 3, pp. 225-39, July 2002.
[13] R. N. Patel, "Application of artificial intelligence for tuning the parameters of an AGC," International Journal of Mathematical, Physical and Engineering Sciences, World Academy of Science, Engineering and Technology (WASET), vol. 1, no. 1, pp. 34-39, 2008.
[14] Earl Cox, Fuzzy Fundamentals. IEEE Spectrum, Oct 1992, pp. 58-61.