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Generation Control of Multi-Area Multi-Source Power System using Fire-Fly Algorithm

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Abstract: This article presents automatic generation control (AGC) of an interconnected three area power system having different production sources such as hydropower, thermal and gas power plants. The control areas are provided with single reheat turbine and generation rate constraints of 3%/min. An attempt has been made to apply a Proportional derivative–Proportional integral derivative (PD–PID) cascade controller in AGC. Controller gains are optimized simultaneously using more robust and powerful evolutionary computational technique Firefly Algorithm (FFA). Performance of classical controllers such as Proportional Integral (PI) and Proportional Integral Derivative (PID) controller are investigated and compared with PD–PID cascade controller. Investigations reveal that PI, and PID provide more or less same response where as PD–PID cascade controller provides much better response than the later. The system dynamic performances are studied with 1% and 2% step load perturbation in Area1. Sensitivity analysis reveals that the FFA optimized PD–PID Cascade controller parameters obtained at nominal condition of loading, size and position of disturbance and system parameter (Inertia constant, H) are robust and need not be reset with wide changes in system loading, size, position of disturbance and system parameters.

Keywords: Automatic generation control, Cascade controller, Fire Fly algorithm, Sensitivity analysis.

I. INTRODUCTION

In automatic generation control (AGC) of interconnected power system the control process highlighted towards the maintenance of system frequency within specified limits around the nominal value, to uphold the scheduled exchange of power between the interconnected areas and to keep each unit's generation at the most economic level. Energy systems on a large scale usually consist of control zones or regions that represent coherent groups of generators. The control area may have a combination of thermal, hydro, gas, nuclear and renewable sources of energy. Researchers around the world are trying to propose several strategies for AGC power systems in order to maintain the system frequency and to balance between the net generation and corresponding loads with losses during the power exchange in their programmed values during normal operation and during small perturbations.

The idea of modeling multi-area interconnected power system has been presented by Elgerd and Fosha [1]. A performance comparison of several classical controllers, such as Integral (I), Proportional-Integral (PI), Integral-Derivative (ID), Proportional-Integral-Derivative (PID) and Integral-Double Derivative (IDD) have been carried out by Saikia et al. [2]. Their investigations reveal the superior performance of IDD controller in two, three and five area thermal systems. However, their studies are limited to single controllers where there is less number of tuning knob. If tuning knobs are more in a controller, there may be possibility of better result from that controller. A two degree of freedom (2DOF) controller named as 2DOF-PID has been introduced by Sahu et al. [3] in AGC. Later on, the performance of a new 2DOF control-ler named as 2DOF- Integral double derivative (2DOF-IDD) has been evaluated by Puja Dash et al. [4].

However, all the above controllers are non cascaded single controllers. In process control, many controllers and control strategies are available. These are suitable for controlling large-scale networked systems. In the con-trolling process, the controllers are either optimized by optimization techniques or self tuned with the help of different control strategies such as model predictive control (MPC), Smith predictor, etc. Yongho Lee et al. [5] proposed a method for PID controller tuning based on process models for cascaded control systems. Cheng et al. [6] have made application of two PID controllers in a cascade control system directly based on the process data collected from a one-shot plant and found it to be the best. Rather than cascade control, many other control approaches generally model based controls are commonly used in process control such as Neural net-work control [7], fuzzy based control [8], MPC [9,10], Smith predictor [13], etc. Saikia [7] has applied the multi layer perception neural network (MLPNN) controller using reinforcement learning in AGC of a three area thermal system. Chown and Hartman [8] has implemented the fuzzy controller in the control ACE (area control error) calculation in AGC, which determines the shortfall or surplus generation that has to be corrected. MPC is a family of controllers in which there is a direct uses of an explicit certain model. It is also described as a class of computer control schemes that utilizes a process model [9,10]. In AGC, the MPC control technique has been applied successfully [11,12] to accomplish the desired control of frequency automatically.

Venkat et al. [11] have designed a distributed model predictive control (MPC) framework for controlling of large-scale networked systems such as AGC of power systems. Liu et al. [12] has employed MPC to control load frequency of a non-reheat type two area thermal systems. The Smith predictor, another popular control in process industry is available in literature [13]. Smith predictor with cascade controller has been used in controlling the temperature of a gas furnace. As these odel based controls have many advantages, also having some limitations such as (a) Modeling of error can essentially influence the performance of the controller, during the tuning of the controller the robustness properties of the resulted control loop must be considered, (b) Its derivation is more complex than the traditional PID controller. [9]. However, the advantages of these model based control processes dominate the limitations. Many research works are present in process control industry, where the performance of cascade controller is improved by incorporating with model predictive control [12], Smith predictor control techniques [13]. This review of literatures gives the limelight towards the heuristically optimized cascade controller which is simple to apply and is investigated in AGC for multi-area single source system.. Hence, this necessitates further investigation on multi-area multi-source system.

Many control and optimization, such as classical, optimal, fuzzy logic (FL), artificial neural networks (ANN), genetic algorithm (GA), bacterial forging, particle swarm, DE are available and most of them are used in AGC to optimize the parameter settings of the controller gain values. Classical technique is a trial and error method and in some cases yields suboptimal results and time consuming [14]. Some literatures exist about the application of supervised artificial neural networks [7, 15] and some authors have used fuzzy logic (FL) controller [8,16] for achieving better performance in AGC. In case of FL controller, more computational time is required for rule base to be formed. In case of neural network, time required for training is more. Modern meta-heuristic algorithms have been developed with an aim to carry out inclusive search, which cannot be solved by classical techniques. The efficiency of meta-heuristic algorithms can be ascribed to the fact that they imitate the best features in nature, especially the selection of the fittest in biological systems, which have evolved by natural selection over millions of years. As given the features or nature of a particular problem, one type of search algorithm may prove to be more efficient than others in solving that particular problem, while the same algorithm may perform poorly in other problems. GA has been applied for optimization of controller gains [16] and recent research identified some of the deficiencies. To overcome the difficulties of local optimum methods, BF [17] technique is used by the researcher for optimization. In [17] the foraging behavior of bacteria is formulated as an optimization technique. Among the modern meta-heuristic algorithm firefly algorithm [12-14] shows more efficient in handling multimodal optimization problem with their fastest search capability and also maintain better exploration balance against exploitation.
In view of above brief literature study, following are the main objectives of the present work.

(a) Optimization of controller gains of several controllers such as PD–PID Cascade, PI and PID controller, when these controllers are considered separately in a three area interconnected system with hydro, thermal and Gas power plant system using FFA.
(b) Comparison of dynamic responses for evaluation of dynamic performances for PD–PID Cascade controller, PI and PID controllers to find the best at nominal conditions and at disturbed conditions.

The system considered is a three equal area interconnected system of capacities Area1: 2000 MW, Area2: 2000 MW, and Area3: 2,000 MW. Each area is equipped with single reheat turbine and generation rate constraints (GRC) of 3% min thermal unit, gas turbines warming and hydraulic turbine in the first instance for the controller design for the system. The linearized models of governors, reheat turbines, hydraulic turbines, gas turbines are used for simulation. The nominal system parameters are taken from [19] and are shown in Appendix A. Per unit values of various parameters of the equal areas are considered to be the same on their respective bases. Hence, in the modeling the interconnected three area system the quantities $a_{12} = P_{r1}/P_{r2}$, $a_{23} = P_{r2}/P_{r3}$, $a_{13} = P_{r1}/P_{r3}$ are taken. Controllers such as PI, PID and PD–PID cascade controllers are considered as separately in this system. The system dynamic performance has been evaluated considering 1% and 2% step load perturbation (SLP) in area1. The transfer model of the two area system is shown in Fig. 1. The model two area system covering hydraulic, thermal units, gas turbines warming and is considered in the first instance for the controller design for the system.

The linearized models of governors, reheat turbines, hydraulic turbines, gas turbines are used for simulation and study LFC power system as shown in Fig. 1. Each unit has its parameter adjustment factor to decide the participation and contribution to the rated load. The sum of the participation factor of each control must be equal to 1. In Fig. 1 R1, R2, R3 are the parameters of regulation, hydraulic and gas thermal units respectively, UT, UH and UG are the outputs of control, thermal hydraulic units and gas respectively, KT, KH and KG are participation factors of thermal, hydro and gas generating units, respectively, is the constant speed governor thermal unit time in seconds, steam turbine time constant in seconds, Kr is the constant reheat steam turbine, is Tr reheat time constant of the steam. turbine sec, is time nominal starting penstock water in seconds, is the regulator of the hydraulic turbine speed reset the time in seconds, is hydro turbine regulator Time constant speed transient fall in s, is hydro turbine main regulator time constant servo speed in seconds, is the time constant standby gas turbine, speed regulator in seconds, and c is the time constant delay of the gas turbine, the speed controller in seconds, is the valve positioner of the gas turbine, is the constant of the gas turbine valve positioner, TF is the gas turbine constant time fuel sec, is the gas turbine time delay combustion reaction sec is the gas turbine compressor discharge at constant volume time in sec gain of power system in Hz/pu MW, is the system time constant power in sec F is the incremental change in the exchange rate and incremental load PD. The nominal system parameters are given in appendix A. Matlab software has been used for simulink model and coding. The variables such as controller gains etc are optimized using Firefly algorithm (FFA). As the change of power between control areas will be minimized quickly, ITAE is a better objective function in studies of AGC and therefore used in this document. The optimization is done to minimize area control error (ACE) using performance index given by Integral Time Absolute error (ITAE)

$$ITAE = \int_0^\infty t \sum_{k=1ton} |ACE_k| dt \quad (1)$$

The area control error (ACE) is indicative of the total interchange of power. Therefore, it is expressed in the following form:

$$ACE = (\Delta P_{i-j} + B_i \Delta f_i)$$

Where ΔP_{i-j} is the change in power from area i to area j. Bi is the tie bias control parameter of area i. Δf_i is frequency deviation in area i. The minimum and maximum bound values of P, I and D Controller are given as 0 and 1.

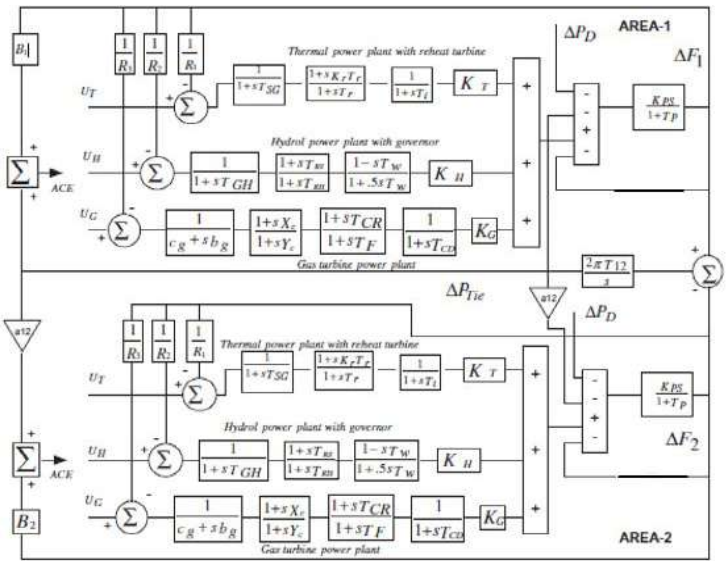

Fig.1. Transfer function model of multiple sources of multiple area

II. FIREFLY ALGORITHM (FFA) FOR OPTIMIZING THE CONTROLLER GAIN VALUES:

Firefly algorithm was developed by Xin-She Yang [18] and it is based on idealized behaviour of the flashing characteristics of fireflies. Nature based algorithms are highly effective and efficient to solve difficult optimization problems. FFA is nature inspired algorithm and gaining popularity recently for solving nonlinear optimization problems technique [18]. For simplicity, we can summarize the flashing characteristics of the FFA as the following three rules: (i) All fireflies are unisex, so that one firefly is attracted to other fireflies regardless of their sex;(ii).Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less bright one will move towards the brighter one. (iii).The attractiveness is proportional to the brightness and they both decrease as their distance increases. If no one is brighter than a particular firefly, it will move randomly. The brightness of a firefly is affected or determined by the landscape of the objective function to be optimized. The movement of a firefly 'i' is attracted to another more attractive (brighter) firefly 'j' is determined by

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2}(x_i - x_j) + \alpha_t \epsilon^t{}_i \qquad (2)$$

In the equation (2) the second term gives the attractiveness of a firefly which varies with the light intensity/brightness seen by adjacent fireflies and the distance between themselves and β_0 is the attraction parameter when the distance is zero. The parameter γwhich characterizes the variation of the attractiveness is the light absorption coefficient and is crucial to determine the speed of convergence of the algorithm. In theory, γ could take any value in the set between 0 to infinity. On the other hand, if $\gamma = 0$, the attraction is constant. If $\beta0 = 0$, it becomes a simple random walk. So, here the value of γ and $\beta0$ was selected by conducting trail and test method. The distance between any two fireflies i and j at x_i and x_j can be the Cartesian distance $r_{ij} = \|x_i - x_j\|_2$. Third term is randomization with α_t being the randomization parameter, and $\epsilon^t{}_i$ is a vector of random numbers drawn from a Gaussian distribution or uniform distribution at time t ($\epsilon^t \varepsilon\ (0,1)$. Here α_t essentially control the randomness (or, to some extent, the diversity of solutions), we can tune this parameter during iterations so that it can vary with the iteration counter t.

So a good way to express α_t is to use$\alpha_t = \alpha_0\delta_t$, where $\delta_t$is $(0 < \delta < 1)$and δ is essentially a cooling factor. Here we use δ = 0.95 to 0.97 and α_0 = 0.01L where L is the scaling parameter depend on the problem. In this work, we use L as 10.Artificial diversification is also applied in the Firefly population to avoid premature convergence, which corresponds to a local optimum. In this work, random movement of firefly is used by simple mutation method like that of used in Genetic Algorithm. In this work, it is assumed that for a given fireflyx, if the dimension O_k is selected, then the resulting dimension will be selected using the equation.

$$O_k = a_k + (b_k - a_k) \times rand \qquad (3)$$

Where , a_k and b_k are lower and upper bands of O_k, rand is a uniform random number chosen in the range of (0, 1)

STUCTURE OF FIREFLY ALGORITHM

Step1: Initialize the objective function as given in Performance Index equation.1
Step2: Initialize a population of fireflies X with the population size of NF x N.
Where
NF is the Number of fireflies as 20
N is the Dimension size depends on the number of Gain Values of the Controller available in the test systems
Step3: The light absorption coefficient is defined as random search between 0 to 10
Step4: While (t<=Max generation (50))
For i=1:n (all n fireflies)
For j=1:i
Light Intensity of each firefly is determined by the objective function
If $I_i > I_j$
Move firefly i towards j in all the dimensions as per the equation (2)
Else
Move firefly i randomly by creating a new dimension as per the equation (3)
End if
Evaluate newly created firefly Light Intensity and update the Light Intensity solutions
End for j
End for i
Rank the fireflies based on its Light Intensity
Extract the Local best firefly (Best Controller Gain value in a iteration) of each population
End While
Step5: Obtain the Global best firefly from all the Local best firefly
End for
End for

III. RESULTS AND DISCUSSION

In this paper, the study of Proportional derivative–Proportional integral derivative (PD–PID) cascade controller in the interconnected three areas AGC has been done with the help of MATLAB simulation. Each area of the system has three production sources such as Hydro, thermal and gas. The controller performance error (ITAE) has been optimized with the help of Fire fly Algorithm (FFA). Maximum iteration of 50 was used during optimization. To check the effectiveness of the PD-PID controller, performance of the PID and PI controller also been simulated in the same three area three source AGC system. To validate the robustness of the PD-PID controller's dynamic performance, two scenarios has been taken in terms of varying 1% and 2% step load perturbation in Area 1. The simulation modeling data of the AGC has been provided in the appendix.

3.1 1% Step Load Perturbation in Area1

The three area system under study with 1% of step load change in area1 is provided with the PI, PID and PD-PID cascade controller separately and in each case the controller gains are optimized with the help of FFA based on the performance measure criteria ITAE and it is given in the table 1.

From the table 1, it is inferred that the performance measure criteria of PD-PID controller is better compared to that of other PI and PID controllers. The statistical analysis results of the AGC system by conducting 20 independent trials are recorded in the table 2. It is evident from the statistical table that the FFA provides better consistency results in terms of quality and iteration convergence

Table.1 Optimal Controller gain values

Area	FFA PI Controller	FFA PID Controller	FFA PI-PID Controller
Area 1	Kp=0.0286 KI= 0.6609	Kp= 0.8550 KI=0.9842 KD=0.3571	Kp=0.7283 KD=0.9830 KP=0.8280 KI=0.9905 KD=0.1691
Area 2	Kp= 0.2625 KI= 0.0204	Kp= 0.6782 KI=0.9979 KD=0.5766	Kp=0.9668 KD=0.1765 KP=0.7623 KI=0.0206 KD=0.38574
Area 3	Kp= 0.0303 KI= 0.1577	Kp=0.8840 KI=0.9726 KD=0.4605	Kp=0.4308 KD=0.9926 KP=0.9297 KI=0.2145 KD=0.7858
ITAE	475.299	166.6046	145.6509

Table. 2 Statistical Performance of FFA

Controller	Worst	Mean	Best	SD	No of Iteration
PID	478.134	476.375	475.299	0.254	13
PID	168.204	167.654	166.604	0.22	6
PD-PID	147.247	146.025	145.651	0.21	6

From the table.2 it is inferred that the Performance error has been reduced with the help of PD-PID controller optimized gains comparatively with the PI, PID controller. The dynamic performance of PI, PID and PD-PID has been obtained for each area and compared. The comparison graph of each area has been shown in fig.2. Fig.2 depicts the controller comparison of change in frequency in area 1 similarly the other two graphs fig.3 and fig.4 depict the controller comparison of change in frequency of area 2 and area 3 respectively.

Table. 3 Dynamic Performance Parameters

Parameter	Controller	Settling Time	Maximum Peak Overshoot
DelF1	FFA PI Controller FFA PID Controller FFA PD-PID Controller	30 20.5 14.8	-0.0175 -0.0125 -0.0125
DelF2	FFA PI Controller FFA PID Controller FFA PD-PID Controller	27 21 20	-0.018 -0.01 -0.0075
DelF3	FFA PI Controller FFA PID Controller FFA PD-PID Controller	28 22 19.8	-0.0185 -0.01 -0.0065

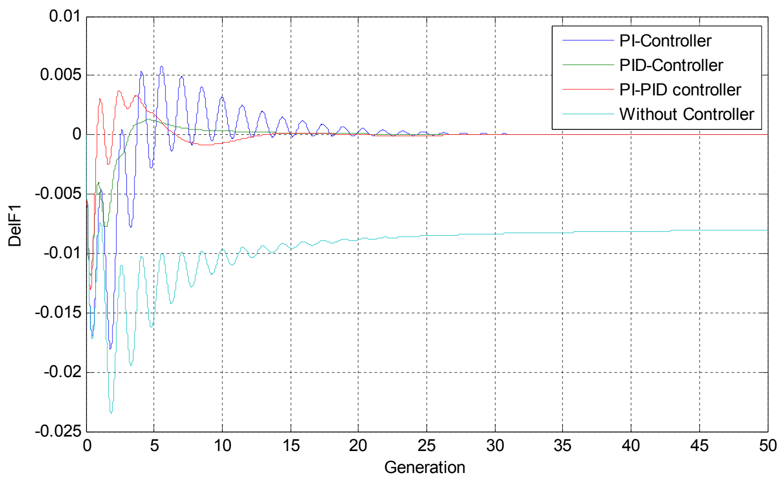

Fig.2 frequency deviation in Area1

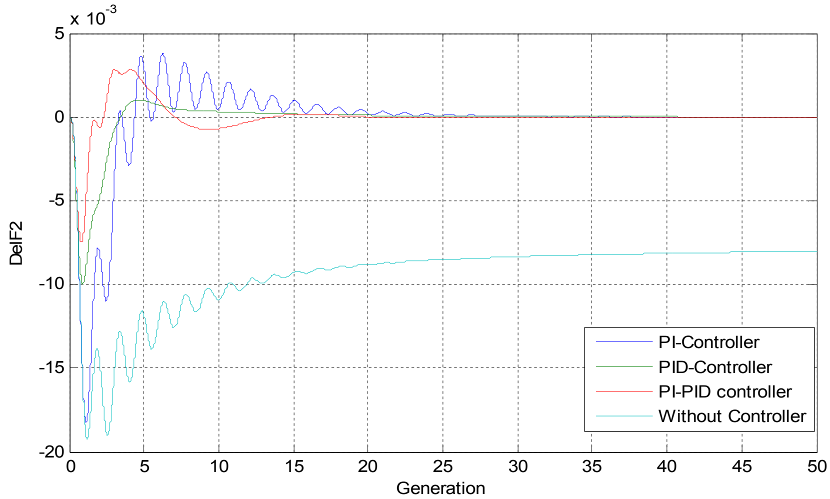

Fig.3 frequency deviation in Area2

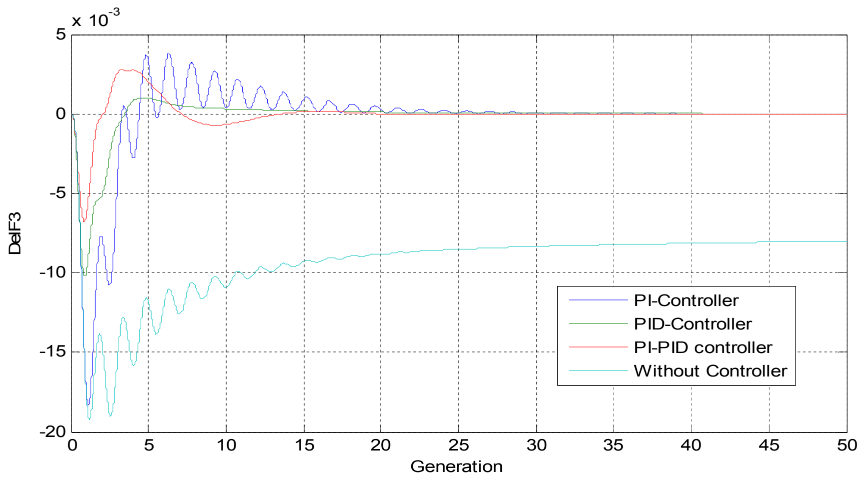

Fig.4 frequency deviation in Area3

From the above dynamic performance graph, parameter such as settling time and maximum peak overshoot has been evaluated and formulated in the table 3. From the table.3 it is inferred that the settling time and peak overshoot of PD-PID controller is better compared to that of PI and PID controller.

3.2 2% Step Load Perturbation in Area1

To check the robustness of the PD-PID controller, three area system has been subject to 2% of step load change in area1.The table.4 provides the optimal gain value of the controller to obtain the minimum ITAE. PD-PID cascaded controller provides minimized ITAE value. The FFA convergence result and its statistical analysis result have been recorded in the table.5. From the table.5 it is inferred that the FFA algorithm provide better solution at the faster convergence rate. The dynamic performance of PI, PID and PD-PID has been obtained for each area and compared.

Table.4 Optimal Controller gain values

Area	FFA PI Controller	FFA PID Controller	FFA PI-PID Controller
Area 1	Kp=0.0286 KI= 0.6609	Kp=0.8184 KI=0.9914 KD=0.4418	Kp =0.9913 KD=0.8452 KP=0.92247 KI=0.9770 KD=0.1889
Area 1	Kp= 0.2129 KI= 0.0063	Kp= 0.5473 KI=0.8986 KD=0.1886	Kp = 0.5776 KD=0.4288 KP=0.4802 KI=0.00295 KD=0.5275
Area 1	Kp= 0.1439 KI= 0.0446	Kp=0.6636 KI=0.6025 KD=0.2748	Kp =0.7915 KD=0.5359 KP=0.8935 KI=0.05969 KD=0.7166
ITAE	217.0069	355.6448	895.5022

The Change in frequency comparison graph of each area has been report in the below fig.5, 6 and 7 for area 1, 2 and 3 respectively. From the above performance graphs it is found that settling time and peak overshoot of PD-PID cascaded controller shows better performance compared to that of PI and PID controller. The above is validated by means of the table .6

Table.5 Statistical Performance of FFA

Controller	Worst	Mean	Best	SD	No of Iteration
PID	900.023	476.375	895.502	0.312	13
PID	358.256	356.021	355.644	0.304	14
PD-PID	220.245	217.56	217.006	0.325	6

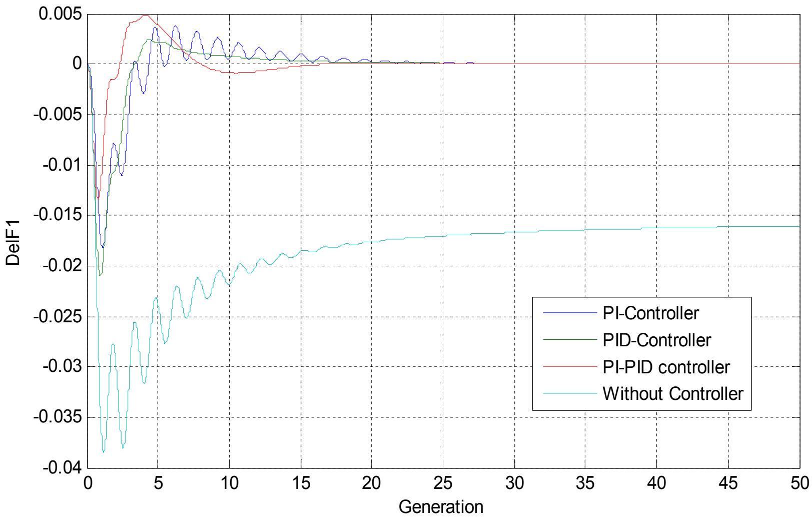

Fig.5 frequency deviation in Area1

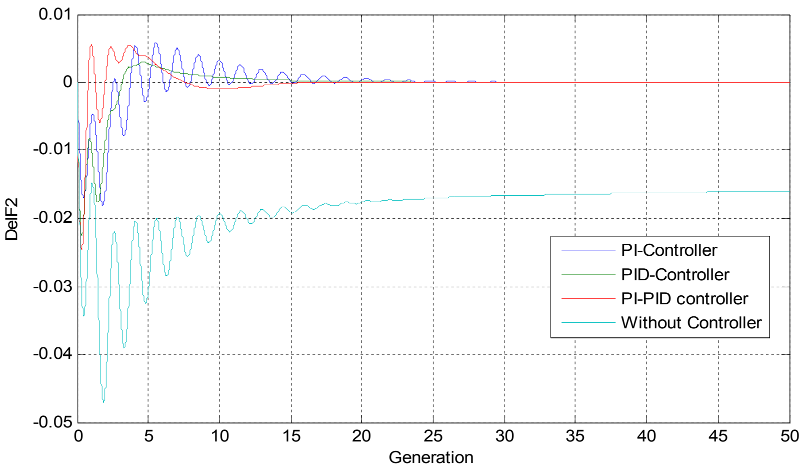

Fig.6 frequency deviation in Area2

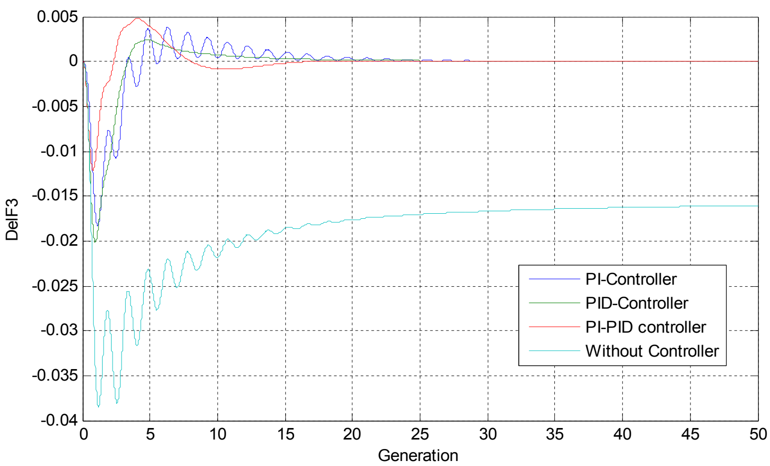

Fig.7 frequency deviation in Area3

Table. 6 Dynamic Performance Parameters

Parameter	Controller	Settling Time	Maximum Peak Overshoot
DelF1	FFA PI Controller FFA PID Controller FFA PD-PID Controller	22.5 18 16	-0.019 -0.021 -0.013
DelF2	FFA PI Controller FFA PID Controller FFA PD-PID Controller	22.5 15 15	-0.018 -0.0225 -0.024
DelF3	FFA PI Controller FFA PID Controller FFA PD-PID Controller	22.5 18 16	-0.019 -0.02 -0.011

IV. CONCLUSION

In this work, PD-PID controller performance has been tested on the three area multisource AGC system using Firefly Algorithm. IT is evident from the above dynamic performance results that the PD-PID controller shows better controllability in maintaining the system nominal parameter such as frequency The results of Firefly algorithm provides better convergence rate and statistical measures. It is evident from the convergence characteristics, that the FFA provides better balance between the exploration and exploitation process at the faster convergence rate

Appendix A:

Nominal parameter of the system are f = 60 Hz;; Nominal SLP = 1%.B1 = B2 = 0.4312 p.u. MW/Hz; Prt = 2000 MW; PL = 1840 MW; R1 = R2 = R3 = 2.4 Hz/p.u.; TSG = 0.08 s; TT = 0.3 s; KR = 0.3; TR = 10 s; KPS1 = KPS2 = KPS3 = 120 Hz/p.u. MW; TPS1 = TPS2 = TPS3 = 11.49 s; T12 = T13 = T23= 0.086 p.u MW/rad; a12 = -1; a13 = -1; a23 = -1; TW = 1 s; TRS = 5 s; TRH = 28.75 s; TGH = 0.2 s; XC = 0.6 s; YC = 1 s; cg = 1; bg = 0.05 s; TF = 0.23 s; TCR = 0.01 s; TCD = 0.2 s; KT = 0.543478; KH = 0.326084; KG = 0.130438; KDC = 1; TDC = 0.2 s.

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