

Regular paper

**Feasible AGC Controllers to Optimize LFC Regulation in Deregulated Power System Using Evolutionary Hybrid Genetic Firefly Algorithm**

*This paper presents the application of feasible AGC controllers for load frequency control in Deregulated power system. The conventional controllers for LFC are primarily integral controller, one major advantage of integral controller is that it reduces the steady state error to zero, but do not perform well under varying operating conditions and exhibits poor dynamic performance. The performance of feedback controller based on optimal control theory, PID controller and fractional order PID Controller based on fractional calculus is investigated on a multi area deregulated power system consisting of Thermal-Thermal unit in area-I, Hydro-Thermal unit in area-II and Thermal-Gas unit in area-III. Using ITAE as performance criteria to be optimize, the controller parameters are optimized using Evolutionary Real coded Genetic algorithm and Firefly algorithm as a Hybrid Genetic-Firefly Algorithm (GA-FA). The main goal of the optimization method is to improve the dynamics of LFC such as improving the transient response of frequency and tie-line power oscillations and to optimize the power generated by various GENCOs according to the bilateral contracts scheduled between GENCOs and DISCOs in an interconnected Multi-area Deregulated power system.*

**Keywords:** AGC Controllers, Bilateral contracts, Deregulated power system, Hybrid GA-FA algorithm, LFC dynamic.

## 1. Introduction

In deregulated scenario, automatic generation control is one of the most important ancillary services to be maintained for minimizing frequency deviations, imbalances of generation and load demand, for regulating tie-line power exchange, facilitating bilateral contracts among various GENCOs and DISCOs and to maintain a reliable operation of the interconnected transmission system in a multi area power system. The requirement to improve the efficiency of power production and delivery and with intense participation of independent power producers motivated restructuring of the power sector. In deregulated scenario, market operators such as independent system operator (ISO) are responsible for maintaining the real time balance of generation and load for minimizing frequency deviations and regulating tie-line flows. The demand being constantly fluctuating and increasing, and hence there is a need to expand the generation by introducing new potential generating plants such as gas fired power plants. The generation of electricity once was handled solely by vertical utility companies, but with the major reforms in oil and natural gas sectors many potential independent power producers has emerged and is catering the growing demand for electricity in their areas without having to build expensive power plants. With the evolution of technologies in gas turbines [6]-[7] combined with steam turbines, provide very high thermal efficiency and thus large capacity systems allowing the combined cycle to emerge as a major source of base load power plants primarily operating on gaseous fuels. The gas turbines due to its fast control can transit from idle to full power in time scale as short as few seconds with a response time of 5-10 seconds for most of intermediate sized gas turbine generating systems, this ability to follow the load rapidly is

\* Corresponding author: <sup>1</sup>S. Farook, Research Scholar, EEE Department, S.V.U College of Engineering, S.V University, Tirupathi-517501, Andhra Pradesh, India, E-mail: farook\_208@yahoo.co.in

<sup>2</sup>Dr. P.Sangameswara Raju, Professor of Electrical Engineering, S.V.U College of Engineering, S.V University, Tirupathi-517501, Andhra Pradesh, India, E-mail:raju\_ps\_2000@yahoo.com

particularly well suitable to provide adequate ancillary services rapidly in deregulated power system.

In this paper the feasible AGC controllers such as feedback controller based on optimal control theory (LQR), conventional Proportional Integral and Derivative (PID) controller and a Fractional Order Proportional Integral and Derivative (FOPID) controller based on fractional order calculus were implemented to investigate the dynamics of load frequency control. Using Integral of time multiplied absolute value (ITAE) of the objective function as the performance criteria the parameters of the controllers were optimized using Genetic algorithm and Firefly algorithm as a Hybrid Genetic-Firefly algorithm (GA-FA).

## 2. Multi area deregulated power system

In a restructured power system environment, with the advent of competitive independent power producers and the flexibility to enter into bilateral transactions between various GENCOs and DISCOs motivated deregulation and evokes new challenging issues in planning and operation of power system. In deregulated power system with unbundling of generation, transmission and distribution invokes various distinct entities such as GENCOs, DISCOs, TRANSCO and ISO [1]-[5]. A deregulated power system in its state consists of suppliers (GENCOs) and buyers (DISCOs) and any transactions between them is represented by the elements of participation matrix [1]- [5], which corresponds to the fraction of total load contracted by any DISCO<sub>j</sub> towards any GENCO<sub>i</sub> in a interconnected power system. Transactions based on the participating suppliers and buyers are classified as POOLco and Bilateral transactions. A DISCO having contracts with GENCOs in its own area is known as *POOL transactions* and with GENCOs of another control area are known as *Bilateral transactions*. In its general form, the participation matrix, DPM represented by eq. (1) is a collection of all possible transactions between the GENCOs and DISCOs and is represented as:

$$DPM = \begin{bmatrix} cpf_{11} & cpf_{12} & \dots & cpf_{1n} \\ cpf_{21} & cpf_{22} & \dots & cpf_{2n} \\ M & M & O & M \\ cpf_{n1} & cpf_{n2} & \dots & cpf_{nn} \end{bmatrix} \quad (1)$$

The sum of all entries in each column of DPM is unity.

$$\sum_i cpf_{ij} = 1 \quad (2)$$

Under steady state the power equations in deregulated environment are,

$$\Delta P_{di} = \Delta P_{Loci} + \Delta P_{uci} \quad (3)$$

Where

$$\Delta P_{Loci} = \sum \Delta P_{Lci} \text{ (Contracted load demand)} \quad (4)$$

The scheduled contracted power exchange in tie-lines is given by:

$$\Delta P_{tie\ ij}^{scheduled} = \text{(Demand of DISCOs in area j from GENCOs in area i)} - \text{(Demand of DISCOs in area i from GENCOs in area j)} \quad (5)$$

The actual power exchanged in Tie-line is given by:

$$\Delta P_{tie\ ij}^{actual} = \frac{2\pi T_{ij}}{S} [\Delta f_i - \Delta f_j] \quad (6)$$

At any time the tie-line power error is given by:

$$\Delta P_{tie\ ij}^{Error} = \Delta P_{tie\ ij}^{actual} - \Delta P_{tie\ ij}^{scheduled} \quad (7)$$

$\Delta P_{tie\ ij}^{Error}$  vanishes in the steady-state as the actual tie-line power flow reaches the scheduled power flow. This error signal is used to generate the respective ACE signals as in the traditional scenario:

$$ACE_i = B_i \Delta f_i + \Delta P_{tie\ ij}^{Error} \quad (8)$$

The total power supplied by  $i^{th}$  GENCO is given by:

$$\Delta P_{gki} = \Delta P_{mki} + apf_{ki} \sum \Delta P_{Uci} \quad (9)$$

Where 
$$\Delta P_{mki} = \sum_{j=1}^N cpf_{ij} \Delta P_{Lcj} \quad (10)$$

$\Delta P_{gki}$  is the desired total power generation of a GENCO<sub>*i*</sub> in area *k* and must track the contracted and un-contracted demands of the DISCOs in contract with it in the steady state. As there are many GENCOs in each area, ACE signal has to be distributed among them due to their ACE participation factor in the LFC task, such that:

$$\sum_{j=1}^{N_i} apf_{ij} = 1 \quad (11)$$

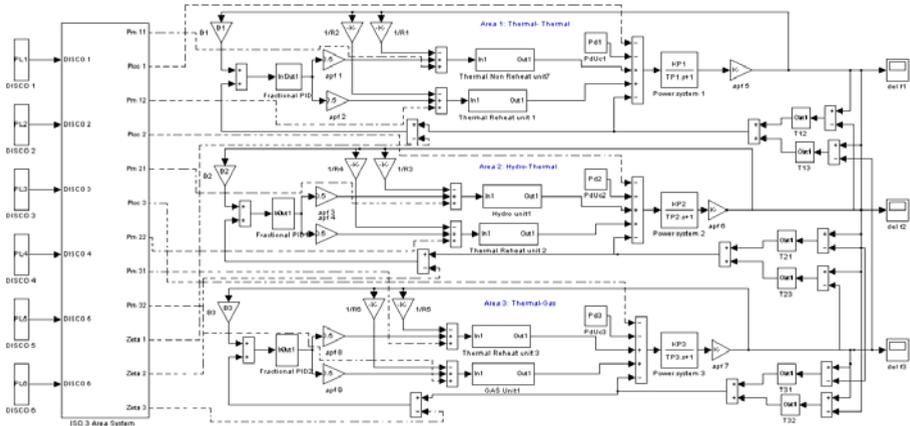


Figure 1. Three area Deregulated Power System

### 3. AGC CONTROLLERS

Most AGC supplementary controllers for load frequency control are primarily composed of an integral controller. The integration gains of the controller are set to level that compromises the dynamic and steady state response of the system. One major advantage of integral controller is that it reduces the steady state error to zero, but do not perform well under varying operating conditions and exhibits poor dynamic performance. The feasible AGC controllers implemented in this paper for LFC are:

#### 3.1. Optimal Feedback Controller

An optimal AGC strategy based on the linear state regulatory theory (LQR) requires the feedback of all state variables of the system for its implementation, and an optimal control

feedback law is obtained by solving the non-linear Riccati equation using suitable computational technique [1]. In practical environment access to all variables is limited and also measuring all of them is impossible. To solve the problem some of the measurable variables are selected for the feedback control law. The three area power system, shown in Fig.1 can be described by the following controllable and observable time-invariant state space representation as:

$$\dot{X} = AX + BU \tag{12}$$

$$Y = CX \tag{13}$$

Where X is the state vector and U is the vector of contracted and un-contracted power demands of the DISCOs.

$$X = \left[ \Delta f_{i...} \quad \Delta P_{gi...} \quad \int ACE_{i...} \quad \Delta P_{tieij...} \right]^T \tag{14}$$

$$\text{and } U = \left[ \Delta P_{li...} \quad \Delta P_{luci...} \right]^T \tag{15}$$

for the system defined by the Eq.(12) and (13), the feedback control law is given as,

$$U = -KY \tag{16}$$

Where K is the feedback gain matrix.

### 3.2. Proportional-Integral and Derivative Controller

The classical Proportional-Integral-Derivative controller is most widely used controller for industrial applications due to its simplicity in realization and tuning. In a PID controller the output control command to the governor, is generally based on the error between set point and some measured process variable. Each element of the PID controller refers to a particular action taken on the error [2]. In LFC problem the frequency deviations and the deviations in the tie-line are weighted together as a linear combination to a single variable called the Area control error (ACE), and is used as a control signal that applies to governor set point in each area. By taking ACE as the system output, the control vector for a PID controller is given by:

$$G_c(s) = - \left[ K_p ACE_i + K_i \int ACE_i dt + \frac{d(ACE_i)}{dt} \right] \tag{17}$$

Where  $K_p$ ,  $K_i$ ,  $K_d$  are the proportional, integral and derivative gains of PID controller.

### 3.3. Fractional Order PID Controller

FOPID controller is a PID controller whose derivative and integral orders are of fractional rather than integer. The extension of derivative and integration order from integer to fractional order provides more flexibility in design of the controller, thereby controlling the wide range of dynamics of a system [11]-[13]. In fractional order controller besides proportional ( $K_p$ ), Integral ( $K_i$ ) and Derivative ( $K_d$ ) constants the controller have additional integral order ( $\lambda$ ), and the derivative order ( $\mu$ ), thus the use of two extra operators adds two more degree of freedom to the controller and makes it possible to further improve the performance of the traditional PID controllers [11]-[13]. Fractional order differential

equation is used to describe the fractional order Proportional-Integral-Derivative controller ( $PI^\lambda D^\mu$ ). The differential equation of fractional order controller is described as

$$U(t) = K_p e(t) + K_i D_i^{-\lambda} e(t) + K_d D_i^\mu e(t) \tag{18}$$

Where  $e(t)$  is the error signal and  $u(t)$  is the control signal. The continuous transfer function of the FOPID controller is given by:

$$G_c(s) = - \left[ K_p + \frac{K_i}{S^\lambda} + K_d S^\mu \right] e(t) \tag{19}$$

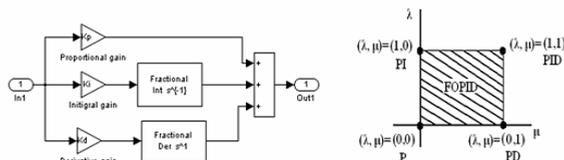


Figure 2. Generalized Fractional Order PID controller

As shown in Fig.2 the FOPID controller generalizes the conventional integer order PID controller and expands it from point to plane. This extension of integral and derivative order will provide much more flexibility and accuracy in PID controller design.

#### 4. Evolutionary hybrid genetic-firefly algorithm

In traditional methods such as sequential optimization approach require several iterations to determine the optimal parameters for an objective function to be optimized. The evolutionary algorithms such as Hybrid Genetic-Firefly algorithms emerges as an alternative for optimizing the controller gains of a multi-area AGC system more effectively than the traditional methods.

##### 4.1. Genetic Algorithm

Genetic algorithm (GA) is an optimization method based on the mechanics of natural selection. In nature, weak and unfit species within their environment are faced with extinction by natural selection. The strong ones have greater opportunity to pass their genes to future generations. In the long run, species carrying the correct combination in their genes become dominant in their population. Sometimes, during the slow process of evolution, random changes may occur in genes. If these changes provide additional advantages in the challenge for survival, new species evolve from the old ones. Unsuccessful changes are eliminated by natural selection. In real-coded genetic algorithm (RCGA), a solution is directly represented as a vector of real parameter decision variables, representation of the solutions very close to the natural formulation of the problem [14]. The efficiency of the GA gets increased as there is no need to encode/decode the solution variables into the binary type.

##### 4.1.1. Chromosome structure

In GA terminology, a solution vector known as an individual or a chromosome. Chromosomes are made of discrete units called genes. Each gene controls one or more features of the chromosome [14]. The chromosome consisting of gains: feedback gain matrix  $K$  for LQR controller,  $K_p$ ,  $K_i$ , and  $K_d$  for a PID controller and  $K_p$ ,  $K_i$ ,  $K_d$ , integral

order ( $\lambda$ ), and the derivative order ( $\mu$ ) operators of FOPID controller is modelled as its genes.

#### 4.1.2. Fitness-Objective function evaluation

The objective here is to minimize the deviation in the frequency and the deviation in the tie line power flows and these variations are weighted together as a single variable called the ACE. The fitness function is taken as the Integral of time multiplied absolute value (ITAE) of ACE [1]-[2]. An optional penalty term is added to take care of the transient response specifications viz. settling time, over shoots, etc. Integral of Time multiplied Absolute value of the Error (ITAE), is given by:

$$ITAE = \int_0^{T_{sim}} t |e(t)| dt \tag{20}$$

Where  $e(t)$ = error considered.

The fitness function to be minimized is given by:

$$J = \int_0^{T_{sim}} (\sum ACE_i) dt + FD \tag{21}$$

$$\text{Where } FD = \alpha_1 OS + \alpha_2 TS \tag{22}$$

Where Overshoot (OS) and settling time (TS) for 2% band of frequency deviation in both areas is considered for evaluation of the FD.

#### 4.1.3. Selection

Selection is a method of selecting an individual which will survive and move on to the next generation based on the fitness function from a population of individuals in a genetic algorithm. In this paper tournament selection is adopted for selection [14].

#### 4.1.4. Crossover

The crossover operation is also called recombination. This operator manipulates a pair of individuals (called parents) to produce two new individuals (called offspring or children) by exchanging corresponding segments from the parent's coding [14]. In this paper simple arithmetic crossover is adopted.

#### 4.1.5. Mutation

By modifying one or more of the gene values of an existing individual, mutation creates new individuals and thus increases the variability of the population [14]. In the proposed work Uniform mutation is adopted.

### 4.2. Firefly Algorithm

The Firefly Algorithm (FA) is a metaheuristic, nature-inspired, optimization algorithm which is based on the social flashing behaviour of fireflies, or lighting bugs. It was developed by Dr. Xin She Yang at Cambridge University in 2007, and it is based on the swarm behaviour such as fish, insects, or bird schooling in nature [8], [15]. Its main advantage is the fact that it uses mainly real random numbers, and it is based on the global communication among the swarming particles i.e., the fireflies, and as a result, it emerges

as an effective for multi objective optimization. The flashing light is produced by a process of bioluminescence, and serves as the functioning signals to attract (communication), mating partners and to attract potential prey. The light intensity at a particular distance from the light source follows the inverse square law. That is as the distance increases the light intensity decreases. Furthermore, the air absorbs light which becomes weaker and weaker as there is an increase of the distance. The flashing light can be formulated in such a way that it is associated with the objective function to be optimized. The main steps of the FA start with initializing a swarm of fireflies, each of which is determined the flashing light intensity. During the iterations a pairwise comparison of light intensity, the firefly with lower light intensity will move toward the higher one. The moving distance depends on the attractiveness. After moving, the new firefly is evaluated and updated for the light intensity. During iteration process, the best-so-far solution is iteratively updated. The pairwise comparison process is repeated until termination criteria are satisfied.

**4.2.1. Population initialization**

Each encoded operation is randomly selected and sequenced until all operations are drawn in order to create a firefly, which represents a candidate solution. The population generated in Genetic algorithm is used as initial population for Firefly algorithm.

**4.2.2. Firefly evaluation**

The next stage is to measure the flashing light intensity of the firefly, which is the objective function to be optimized. The objective functions defined by the equations (20) to (22) were used for evaluation the light intensities of the fireflies.

**4.2.3. Attractiveness**

As light intensity decreases with the distance from its source and light is also absorbed in the media, so we should allow the attractiveness to vary with degree of absorption. The light intensity  $I(r)$  varies with distance  $r$  monotonically and exponentially. That is:

$$I = I_0 e^{-\gamma r} \tag{23}$$

Where  $I_0$  the original light intensity and  $\gamma$  is the light absorption coefficient. As firefly attractiveness is proportional to the light intensity seen by adjacent fireflies, thus the attractiveness  $\beta$  of a firefly can be defined by:

$$\beta = \beta_0 e^{-\gamma r^m} \quad m > 1 \tag{24}$$

Where,  $r_{ij}$  is the distance between any two fireflies,  $\beta_0$  is the initial attractiveness at  $r = 0$ , and  $\gamma$  the absorption coefficient which controls the decrease of the light intensity.

**4.2.4. Distance**

The distance between any two fireflies  $i$  and  $j$ , at positions  $x_i$  and  $x_j$ , respectively, can be defined as a Cartesian or Euclidean distance as follows:

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^d (x_{i,k} - x_{j,k})^2} \tag{25}$$

**4.2.5. Movement**

The movement of a firefly  $i$  which is attracted by a more attractive (i.e., brighter) firefly  $j$  is given by the following equation:

$$x_{i+1} = x_i + \beta_0 e^{-\gamma r^2} (x_i - x_j)^2 + \alpha(rand - 0.5) \tag{26}$$

The second term is due to the attraction while the third term is the randomization with  $\alpha$  being the randomization parameter.

### 4.3. Hybridization

The main motivation for the hybridization of different algorithmic concepts has been to obtain better performing systems that exploit and combine advantages of the individual algorithm strategies, i.e., Genetic algorithm (GA) and Firefly algorithm (FA). The hybridization of the algorithm is carried out in two phases; first the diversification of the algorithm to search the optimal solution in the search space is achieved by using the genetic operators such as selection, crossover and mutation operations. Secondly the precession of the algorithm to search the optimal solution is intensified by using the swarm behaviour of the Firefly algorithm. Firefly algorithm has some disadvantage such as trapping into several local optimums. Firefly algorithm do local search as well and sometimes can't get rid of them. Firefly algorithm parameters are set fixed and they do not change by the time. In order to enhance global search and generate new solutions in Firefly algorithm is combination of genetic algorithm with firefly algorithm as a new generation which may find better solutions and make a balance between global and local search

Schematically, the hybrid Genetic-Firefly algorithm (GA-FA) can be summarized as the pseudo code:

*Initialization:*

*Define the FA parameters  $\alpha$ ,  $\gamma$ ,  $\beta_0$ .*

*Define GA parameters  $p_c$ ,  $p_m$*

*Define the objective function  $F(x)$ :*

*Generate initial population of fireflies  $x_i$ ;  $i=1,2,\dots,n$*

*Light intensity / Fitness value of population  $i$  is determined by objective function  $F(x_i)$*

*While  $itr \leq Maxgen$*

*Apply evolutionary Genetic algorithm operators*

*Selection: Select the individuals, called parents that contribute to the population at the next generation. Tournament selection is adopted in the algorithm.*

*Crossover: Generate an offspring population Child,*

*if  $pc > rand$ ,*

*Choose one best solutions  $x$  from the population based on the light intensity/fitness value and random solution  $y$  from the population for crossover operation. Using arithmetic crossover operator, generate offspring and add them back into the population.*

*Child<sub>1</sub> =  $r * parent_1 + (1 - r) * parent_2$ ;*

*Child<sub>2</sub> =  $r * parent_2 + (1 - r) * parent_1$ ;*

*end if*

*Mutation: Mutation alters a parent, to produce a single new individual child.*

*if  $pm > rand$ ,*

*Mutate the selected solution with predefined mutation rate.*

*end if*

*for  $i=1:n$*

*for  $j=1:n$*

*Light intensity  $I(x)$  is determined by objective function  $F(x_i)$*

*If  $I_i < I_j$*

*Then move firefly  $i$  towards firefly  $j$  (move towards brighter one)*

*end if*

*Attractiveness varies with distance  $r$  via  $\exp[-\gamma r]$*

*Evaluate new solutions and update light intensity*  
*end for j loop*  
*end for i loop*  
*Fitness assignment: Evaluate new solutions and update light intensity.*  
*Stopping criterion: If the maximum number of generations has reached then terminate the search otherwise go to next iteration*  
*end while*  
*end*

**5. Simulation**

To investigate the performance of the controllers, a three-area interconnected power system consisting of Thermal-Thermal unit in area-I, Hydro-Thermal unit in the area-II and Thermal-Gas unit (GAST modal) in area-III is considered. In each area two GENCOs and two DISCOs are considered with each GENCO demanding a load demand of 0.1puMW contracted towards the GENCOs according to the bilateral contracts established between various GENCOs and DISCOs. Using ITAE as performance criteria to be optimize, feedback gain matrix K for LQR controller,  $K_p$ ,  $K_i$ , and  $K_d$  for a PID controller and  $K_p$ ,  $K_i$ ,  $K_d$ , integral order ( $\lambda$ ), and the derivative order ( $\mu$ ) operators of FOPID controller are optimized using proposed Evolutionary Hybrid Genetic-Firefly algorithm. The simulation is done in MATLAB / SIMULINK platform. The GAST model [6]-[7] for simulation studies describing the dynamic behaviour of gas power turbine governor systems is shown in fig.3

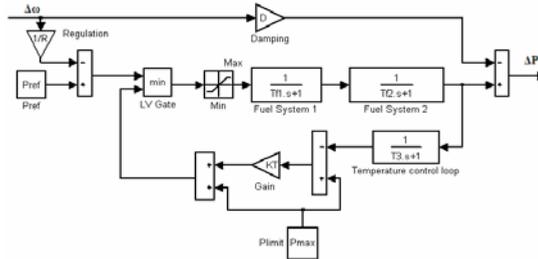


Figure 3. GAST Governor model

The GENCOs in each area participates in ACE defined by the following  $apf_s$ :

$$\begin{array}{lll}
 apf_1= 0.5 & apf_3= 0.5 & apf_5= 0.5 \\
 apf_2= 1-apf_1=0.5 & apf_4=1-apf_3=0.5 & apf_6=1-apf_5=0.5
 \end{array}$$

**5.1. Bilateral Transactions**

In this scenario, DISCOs have the freedom to have a contract with any GENCO in their or another areas. Consider that all the DISCOs contract with the available GENCOs within the area and with interconnected areas for power as per following DPM. All GENCOs participate in the LFC task. It is assumed that a large step load 0.1 pu MW is demanded by each DISCOs in three areas according to the bilateral contracts:

$$DPM = \begin{bmatrix} 0.25 & 0.00 & 0.25 & 0.00 & 0.50 & 0.00 \\ 0.50 & 0.25 & 0.00 & 0.25 & 0.00 & 0.00 \\ 0.00 & 0.50 & 0.25 & 0.00 & 0.00 & 0.00 \\ 0.25 & 0.00 & 0.50 & 0.75 & 0.00 & 0.00 \\ 0.00 & 0.25 & 0.00 & 0.00 & 0.50 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 1.00 \end{bmatrix}$$

The frequency deviations of three areas, GENCOs power generation, Tie-line power flow and Area control error for the given operating conditions is depicted in Fig.4 to Fig.6.

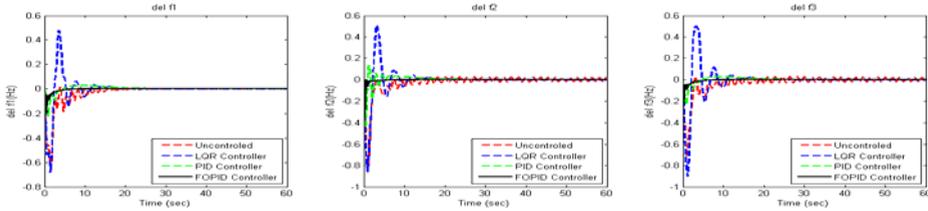


Figure 4. Frequency deviations in three areas

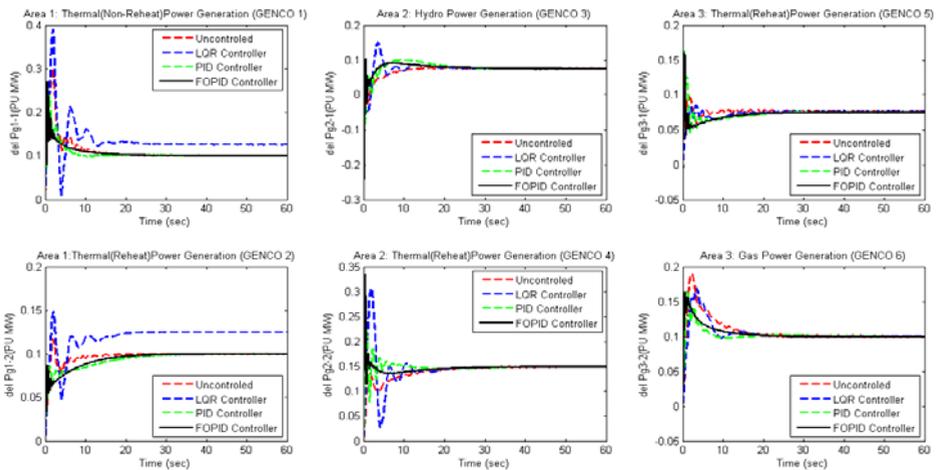


Figure 5. GENCOs Power Generation

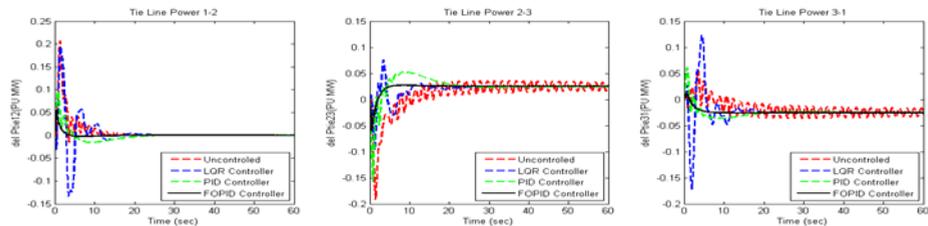


Figure 6. Tie-line Power exchange in tie-lines

## 6. Results and discussions

The dynamic performance of multi area deregulated power system is investigated for comparison. Fig. 4 demonstrated the frequency deviations in three areas, following a load

demand of 0.1 pu MW step load demand contracted by each DISCO in three areas. It can be seen that the dynamics of the frequency with respect to its peak overshoot and settling time is improved by FOPID controller considerably compared with Feedback controller and PID controller and at steady state the frequency of each GENCOs is back to its nominal values. Fig.5 shows the change in generation of GENCOs according to the schedule governed by the ISO. It can be observed that the generation of GENCOs in area I converged by controller based on LQR couldn't settle to the schedule laid by ISO, this is because the controllers based on optimal control and variable structure control needs feedback of most of state variables of the system which is practically difficult to have access and measure them in a large interconnected system and thus have steady state error. Due to the bilateral contracts existing between GENCOs and DISCOs of interconnected areas, the tie-line power converges to scheduled values at steady state shown in Fig.6. The generation of various GENCOs and tie-line power in the interconnectors is summarized in table-1.

Table I. GENCOs power generation and Tie-line power exchange

	Scheduled	LQR Control	PID Control	FOPID Control
GENCO 1	0.100	0.125	0.100	<b>0.100</b>
GENCO 2	0.100	0.125	0.100	<b>0.100</b>
GENCO 3	0.075	0.075	0.075	<b>0.075</b>
GENCO 4	0.150	0.149	0.150	<b>0.150</b>
GENCO 5	0.075	0.0751	0.075	<b>0.075</b>
GENCO 6	0.100	0.100	0.100	<b>0.100</b>
del Ptie 1-2	0.000	0.000	0.000	<b>0.000</b>
del Ptie 2-3	0.025	0.025	0.025	<b>0.025</b>
del Ptie 3-1	-0.025	-0.025	-0.025	<b>-0.025</b>

The time domain specifications such as overshoot and settling time of frequency dynamics for the given operating conditions are tabulated in table II. The various performance measures for frequency deviations are calculated for the considered operating conditions and the results are tabulated in table III.

Table II. Time domain Specifications

	Uncontrolled		LQR Control		PID Control		FOPID Control	
	Max. freq deviation	Settling time						
del $f_1$	0.6722	55.2985	0.6822	18.9474	0.2175	29.2568	<b>0.1899</b>	<b>7.9312</b>
del $f_2$	0.8437	59.7761	0.8562	22.1053	0.4412	26.0811	<b>0.2301</b>	<b>8.4003</b>
del $f_3$	0.7145	59.7761	0.9029	23.6842	0.2301	27.0270	<b>0.2197</b>	<b>8.6582</b>

Table III. Performance measures

	Uncontrolled		LQR Control		PID Control		FOPID Control	
	IAE	ITAE	IAE	ITAE	IAE	ITAE	IAE	ITAE
del $f_1$	0.9966	5.7793	1.0417	5.2017	0.3959	2.9015	<b>0.1175</b>	<b>0.3636</b>
del $f_2$	1.5446	20.851	1.1406	5.4076	0.5697	3.1457	<b>0.1089</b>	<b>0.2974</b>
del $f_3$	1.3324	19.834	1.3664	6.8013	0.4254	2.9809	<b>0.1251</b>	<b>0.3733</b>

The convergence characteristics of individual GA, Firefly and Hybrid GA-FA techniques are depicted in Fig. 7. From the characteristics it is clear that the hybrid genetic-firefly algorithm convergence to optimal solution within less number of iterations compared to the individual strategy.

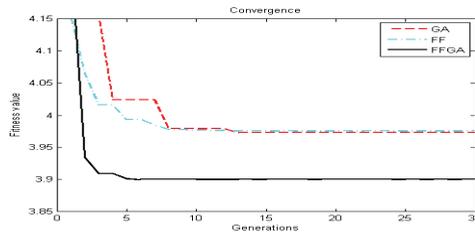


Figure 7. Convergence characteristics

## 7. Conclusions

The feasible supplementary controllers for improving the overall dynamics of LFC in the restructured power system are implemented in this paper. Using ITAE as performance criteria the controller parameters are optimized using Evolutionary Genetic and Firefly algorithm as a hybrid algorithm. From simulation results the dynamic response obtained for the scenario considered, it is inferred that the implementation of FOPID controller optimized by Evolutionary GA-FA Algorithm results in an appreciable improvement in dynamics of frequency and tie-line oscillations, reduction in magnitude of overshoot, converging to the nominal values at steady state within convincing settling time over PID and feedback controllers. The simulation results also show the ability of the controller to track the load effectively scheduled by ISO and holding the frequency of GENCOs and tie-line power in the interconnectors at their nominal values. The proposed GA-FA algorithm combines the potential advantage of individual genetic algorithm and firefly algorithm to find the optimal solution and make a balance between global and local search. The overall performance of FOPID controller tuned by the proposed algorithm exhibits improved dynamic performance over conventional PID and Feedback controller over a wide range of operating conditions.

## References

- [1] Elyas Rakhshani, Javad Sadeh., "Practical viewpoints on load frequency control problem in a deregulated power system", *Energy Conversion and Management*, Jan-2010, No. 51, pp. 1148–1156.
- [2] Karnavas Y.L., Dedousis K.S., "Overall performance evaluation of evolutionary designed conventional AGC controllers for interconnected electric power system studies in a deregulated market environment", *International journal of Engineering Science and Technology*, 2010, Vol. 2, No. 3, pp. 150-166.
- [3] Janardan Nanda, S. Mishra, Lalit Chandra Saikia., "Maiden application of Bacterial Foraging based optimization technique in multiarea Automatic generation control.", *IEEE Transactions on power systems*, May- 2009, Vol. 24. No.2, pp. 602-609.
- [4] Donde V, Pai M.A, Hiskens I., "Simulation and Optimization in an AGC System after Deregulation.", *IEEE Transactions on Power Systems*, August 2001, Vol. 16, No. 3, pp.481-489.
- [5] Emilia Nobile, Anjan Bose., "Feasibility of a Bilateral Market for Load Following.", *IEEE Transactions on Power systems*, November 2001, Vol. 16, No. 4, pp. 782-787.
- [6] Soon Kiat Yee, Jovica V. Milanovic', and F. Michael Hughes; "Overview and Comparative Analysis of Gas Turbine Models for System Stability Studies"; . *IEEE Transactions on Power Systems*, Vol. 23, NO. 1, February 2008; PP: 108-118.
- [7] Naoto Kakimoto, and Kazuhiro Baba., "Performance of Gas Turbine-Based Plants during Frequency Drops.", *IEEE Transactions on Power systems*, Aug. 2003, Vol. 18, No. 3, pp. 1110-1115.
- [8] X. S. Yang, "Firefly algorithms for multimodal optimization," in *Proceedings of the Stochastic Algorithms: Foundations and Applications (SAGA '09)*, vol. 5792 of *Lecture Notes in Computing Sciences*, pp. 169–178, Springer, Sapporo, Japan, October 2009.
- [9] Sh. M. Farahani, A. A. Abshouri, B. Nasiri, and M. R. Meybodi., "A Gaussian Firefly Algorithm.", *International Journal of Machine Learning and Computing*, Dec. 2011, Vol. 1, No. 5, pp. 448-453.

- [10] N. Chai-ead, P. Aungkulanon, and P. Luangpaiboon., “Bees and Firefly Algorithms for Noisy Non-Linear Optimisation Problems.”, *Proceedings of the International Multi Conference of Engineers and Computer scientists*, March 2011, Vol.2, pp. 1449-1454.
- [11] Arijit Biswas, et.al: “Design of fractional-order  $PI^{\lambda}D^{\mu}$  controllers with an improved differential evolution”, *Engineering Applications of Artificial Intelligence.*, Volume: 22 (2009) 343–350.
- [12] HongSheng Li, Ying Luo, and YangQuan Chen: “A Fractional Order Proportional and Derivative (FOPD) Motion Controller:Tuning Rule and Experiments”, *IEEE Transactions on control systems technology*, Vol. 18, No. 2, March 2010; PP: 516-520.
- [13] Ali Akbar Jalali, Shabnam Khosravi: “Tuning of FOPID Controller Using Taylor Series Expansion”., *International Journal of Scientific & Engineering Research.*, Volume 2, Issue 5, May-2011; ISSN 2229-5518.
- [14] D. Goldberg, *Genetic algorithms in search, optimization, and machine learning*. Addison-wesley, 1989.
- [15] X. S. Yang, *Nature-Inspired Meta-Heuristic Algorithms*, Luniver Press, Beckington, UK, 2008.