AGC of CCGT plant

SHASHI KANT SAHU

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Automatic generation control of a combined cycle gas turbine plant with classical controllers using Firefly Algorithm

Lalit Chandra Saikia *, Shashi Kant Sahu

Department of Electrical Engineering, National Institute of Technology Silchar, Assam, India

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ABSTRACT

In this paper, a first attempt has been made to develop a small perturbation model to study the frequency response of a combined cycle gas turbine (CCGT) power plant, following a small step load perturbation (SLP). The powerful Firefly Algorithm (FA) has been used for the first time in frequency control in CCGT plant for optimization of controller gains. The performance of some classical controllers such as integral (I), Proportional–Integral (PI), Proportional–Integral–Derivative (PID) and Integral–Derivative (ID) are compared, and it is found that PID controller gives better performance over the other controllers. Sensitivity analysis has been carried out to see the robustness of the optimum PID gains obtained at nominal to wide change in loading and change in inertia constant (*H*). Analysis reveals that optimized PID gains obtained at nominal are quit robust and need not be reset for wide changes in loading and inertia constant (*H*).

1. Introduction

In large power system, the generation of power is normally done by thermal, hydro and nuclear power plant. In order to achieve the reliability in power system operation, it is necessary to maintain the electric energy system at a desired operating level characterized by nominal frequency, voltage profile and load flow configuration. Since last some decades, the interest over combined cycle gas turbine (CCGT) power plants has been increased to a greater extent in the large power system. This is due to its higher efficiency, greater flexibility, faster response capability, and lower emission than other conventional plants. In spite of this, the installation of CCGT plant is less costly and also it takes shorter installation time than other power plants. Loss of a large load or generation can lead to a rapid decrease in the system frequency especially in a small system if the system is operated with an insufficient generation reserve. The CCGT power plants have a very important role in ensuring the normal operational status of the power systems. For a system having a large proportion of power from CCGT plant, understanding of dynamic behavior of the plant under small perturbation is important. Gas turbine can respond to disturbance with quicker reaction time than steam turbine in sliding pressure mode. i.e. operation with steam control valves fully open. Due to the storage capacity of their heat recovery method steam generator as well as steam turbine presents a slower reaction time. Studies in the Refs. [1–3] mainly focused on the governor primary controller. Till date no attention has been paid to study the performance of the governor secondary controller on CCGT plant which needs further investigations.

A number of approaches for control and optimization such as classical, optimal, bacterial foraging (BF) [4–7], fuzzy logic (FL) [4], genetic algorithm (GA) [8], particle swarm optimization (PSO) [9], artificial neural network (ANN) [10], and artificial bee colony (ABC) [11] techniques have been used for control and optimization of controller's parameters. For any optimization technique both the convergence and optimal value achieved are important. Classical approached based on integral squared error (ISE) is quite involved and time consuming and most of the cases provide suboptimal result. Recent research has identified some of the deficiencies in GA performance [4]. The premature convergence of GA degrades its efficiency and reduces the search capability. To overcome this BF technique [5] is available in which the number of parameters that are used for searching the total solution space is much higher compared to those in GA. Like GA, PSO is also less susceptible to getting trapped on local optimum [7]. The authors in [7] have shown that performance of BF is better than PSO in terms of convergence, robustness and precision. The authors in [11] clearly shows that the tuning performance of ABC algorithm is better than PSO algorithm. Recently a new metaheuristic algorithm known as "Firefly Algorithm" (FA) is available in the literature [12,13]. The FA is inspired by the flashing behavior of fireflies. Resent research show that FA is a very efficient and could outperform other metaheuristic algorithms [14]. FA can find the global optima as well as all the local optima simultaneously in a

* Corresponding author. Tel.: +91 9435173835; fax: +91 3842 233797.
E-mail addresses: lcsaikia@yahoo.com (L.C. Saikia), shashi0525@gmail.com (S.K. Sahu).

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Nomenclature

N	speed (RPM)
R	governor speed regulation parameter (pu MW/Hz)
T_g	governor time constant (s)
K_4	first gain of radiation shield
K_5	second gain of radiation shield
T_4	thermocouple time constant (s)
K_3	ratio of fuel adjustment
T_v	valve positioned time constant (s)
T_{cd}	compressor volume time constant (s)
T_m	tube metal heat capacitance time constant for waste recovery boiler (s)
T_b	boiler storage time constant (s)
T_{igv}	inlet guide vane time constant (s)
K_p	gain of power system
T_p	power system time constant (s)
$*$	optimum values
K_{PAIR}, K_{PTEMP}, K_{PSEC}	proportional gains of air flow, temperature and secondary controllers respectively
K_{IAIR}, K_{ITEMP}, K_{ISEC}	integral gains of air flow, temperature and secondary controllers respectively
K_{DAIR}, K_{DTEMP}, K_{DSEC}	derivative gains of air flow, temperature and secondary controllers respectively

very effective manner. A further advantage of FA is that different fireflies will work almost independently, it is thus particularly suitable for parallel implementation [14]. Senthilnath et al. [15] show the superiority of FA in clustering over other two nature inspired techniques – ABC and PSO and also proved that FA technique is efficient, reliable and robust method. Yang et al. [16] show the superiority of FA over BF, PSO and other approaches in terms of the solution quality and reliability based on the simulation results and also show the robustness and capability of FA in complex optimization problems. Surprisingly, this algorithm is not used in frequency control. This needs further investigations.

Though, the performances of several classical secondary controllers are evaluated in conventional system [6,8,9,11] till date no such investigations have been done in frequency control of an isolated CCGT plant.

Sensitivity analysis has been carried out to demonstrate the robustness of the optimum controller gains obtained at nominal condition in many literatures [4,6] the same is not done in small signal model of CCGT plant.

In view of the above, following are the main objectives of the present work.

(a) To study the combined cycle gas plant behavior and characteristics and to develop a small signal model of CCGT in Matlab.
(b) To apply Firefly Algorithm for simultaneous optimization of controller gains of several classical controllers such as Integral (I), Proportional–Integral (PI), and Integral–Derivative (ID and Proportional–Integral–Derivative (PID) in the CCGT model.
(c) To compare the dynamic performances of the controllers in (b) to find the best controller.
(d) To find the robustness of the optimum gains of the best controller obtained at nominal condition to wide changes in loading and inertia constant.

2. Combined cycle power plant model

A combined cycle power plant combines more than one thermodynamic cycle. A combined cycle gas turbine power plant employs Brayton cycle and Rankine cycle, in which a gas turbine generator generates electricity and heat in the exhaust, is used to make steam, which in turn drives a steam turbine to additional electricity. So it can achieve high energy efficiency. The plant mainly consists of a compressor, combustor, gas turbine, steam turbine, waste heat recovery boiler and a generator.

Air is sucked by the compressor and compresses it, and sends it to the combustor. This high pressure air burns with fuel to make high temperature and high pressure combustor gas. This combustor gas drives the gas turbine. The waste heat recovery boiler collects some energy of exhaust gas, and drives the steam turbine. Plant power output is the sum of the gas turbine and the steam turbine power outputs. The gas turbine produces about two thirds of the total power output, and the steam turbine produces the rest.

Literature survey shows that a lot of works have been reported in developing the models of the gas turbine and all are based on the model developed by Rowen [17,18]. The first model introduced by Rowen has not considered the airflow control through inlet guide vane (IGV) but later it is included. Temperature effects on CCGT plant output are very important for analyzing the performance of the unit. Authors in [19] have studied the variation of combined cycle plant parameters with temperature control. In [20–23] authors describes development of combined cycle plant models and its control. The mathematical model governing the CCGT plant [2] is reproduced below for easy reading and deriving the small signal model in the next section.

The air in the compressor used in a CCGT plant is adiabatically compressed. The compression ratio can be calculated from the following equation:

$$x = (P_{r0} W_a)^{\frac{\gamma-1}{\gamma}} \tag{1}$$

where P_{r0} is the compressor pressure ratio, W_a is the air flow (kg/s), and γ is the specific heat ratio. The compressor discharge temperature T_d can be represented by the following equation:

$$T_d = T_i\left(1 + \frac{x-1}{\eta_c}\right) \tag{2}$$

where T_i is the ambient temperature and η_c is the compressor efficiency. Using T_d, the gas turbine inlet temperature T_f can be represented by the following equation:

$$T_f = T_d + K_2 \frac{W_f}{W_a} \tag{3}$$

where K_2 is a constant and W_f is the fuel flow (kg/s). Using T_f, the exhaust gas temperature T_e can be obtained through the following equation:

$$T_e = T_f\left[1 - \left(1 - \frac{1}{x}\right)\eta_T\right] \tag{4}$$

where η_T is the turbine efficiency. Moreover, the power supplied to the gas turbine and steam turbine can be calculated using (5) and (6) respectively.

$$P_g = K_g W_f \tag{5}$$

$$P_s = K_s W_a T_e \tag{6}$$

where K_g and K_s are the gas turbine and steam turbine output coefficient respectively. Fig. 1 shows how the combined cycle plant vari-

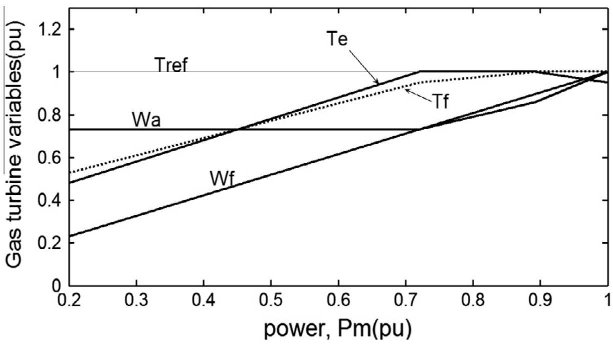

Fig. 1. Heat balance diagram in a CCGT system.

ables vary with the plant output. As the power output of plant increases, W_f increases which results in increase in T_e (Eqs. (3) and (4)). When $T_e = T_{ref}$, the air flow controller increases the W_a according to W_f such that the power demand is meet, as well as T_e remains at T_{ref}.

From Fig. 1 we can see that when the load is around 70% of the full load value the T_e gets saturated to its maximum value T_{ref}. Since in case of CCGTs we also use a steam turbine its efficiency will be higher if we have a higher T_e. Therefore, in order to achieve optimal efficiency in CCGTs, the exhaust gas temperature should be maintained at the maximum allowable level [3]. Hence, in case of CCGT plant it is generally proposed to operate between 70% and 100% loading condition for achieving maximum energy efficiency leading to a lesser per unit fuel cost [3].

3. Small signal modeling of CCGT plant

The equations for the small signal modeling are developed by perturbing the gas turbine Eqs. (1)–(6). The perturbed equations of Eqs. (1)–(6) are shown below

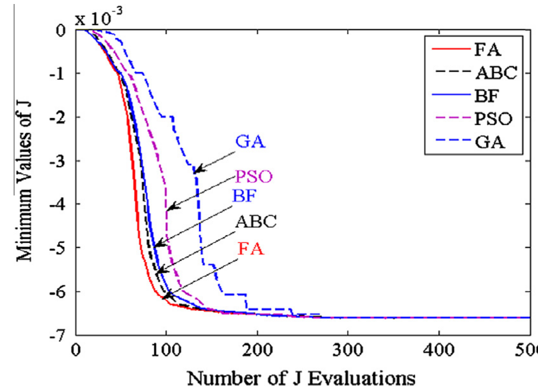

Fig. 3. Convergence characteristics of GA, PSO, BF, ABC, and FA algorithm.

Table 1
Optimum value of different controllers gains at nominal condition.

Optimum gains	Controllers			
	PID	PI	ID	I
K^*_{ITEMP}	0.0440	0.0070	0.0196	−0.0642
K^*_{IAIR}	4.0266	1.1129	1.3944	1.5453
K^*_{ISEC}	0.2283	0.1778	0.2199	0.1674
K^*_{PTEMP}	7.0402	4.6005		
K^*_{PAIR}	6.8588	8.2639		
K^*_{PSEC}	0.1185	0.2030		
K^*_{DTEMP}	0.0641		0.0317	
K^*_{DAIR}	0.0264		0.0483	
K^*_{DSEC}	0.1260		0.1575	

$$\Delta x = (P_{r0})^{\frac{\gamma-1}{\gamma}} \left(\frac{\gamma-1}{\gamma}\right) \frac{1}{W_{a0}^{\frac{1}{\gamma}}} \Delta W_a \tag{7}$$

$$\Delta T_d = T_i \frac{\Delta x}{\eta_c} \tag{8}$$

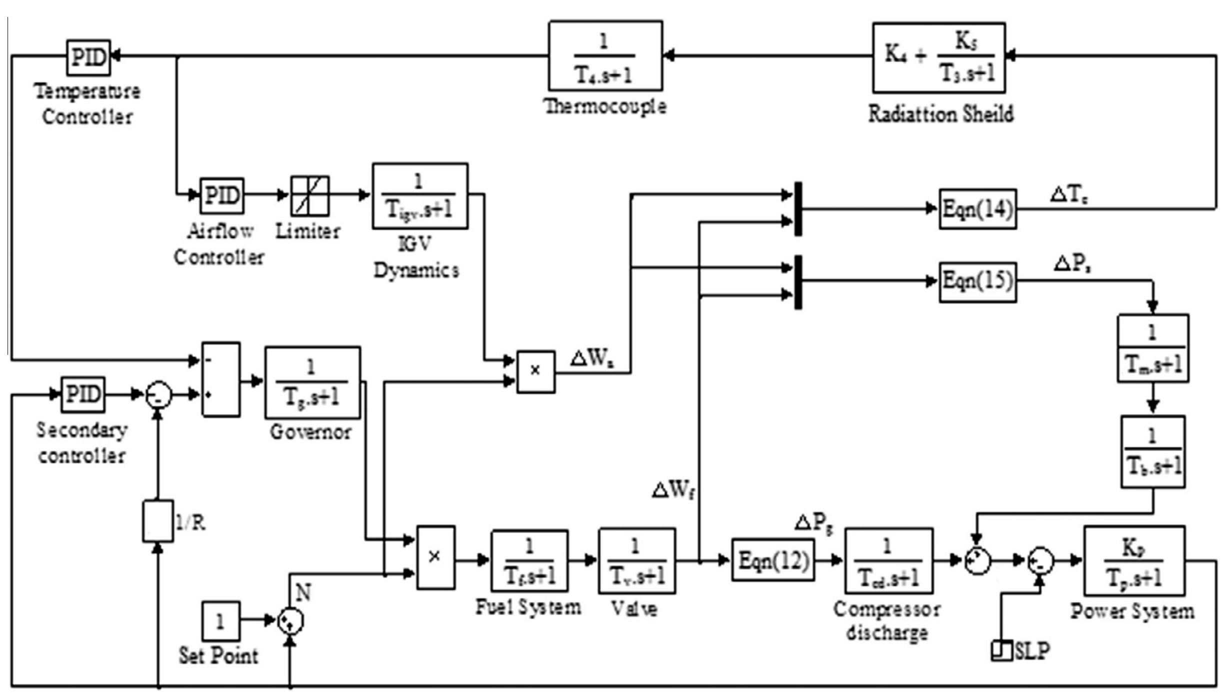

Fig. 2. Transfer function model of CCGT plant.

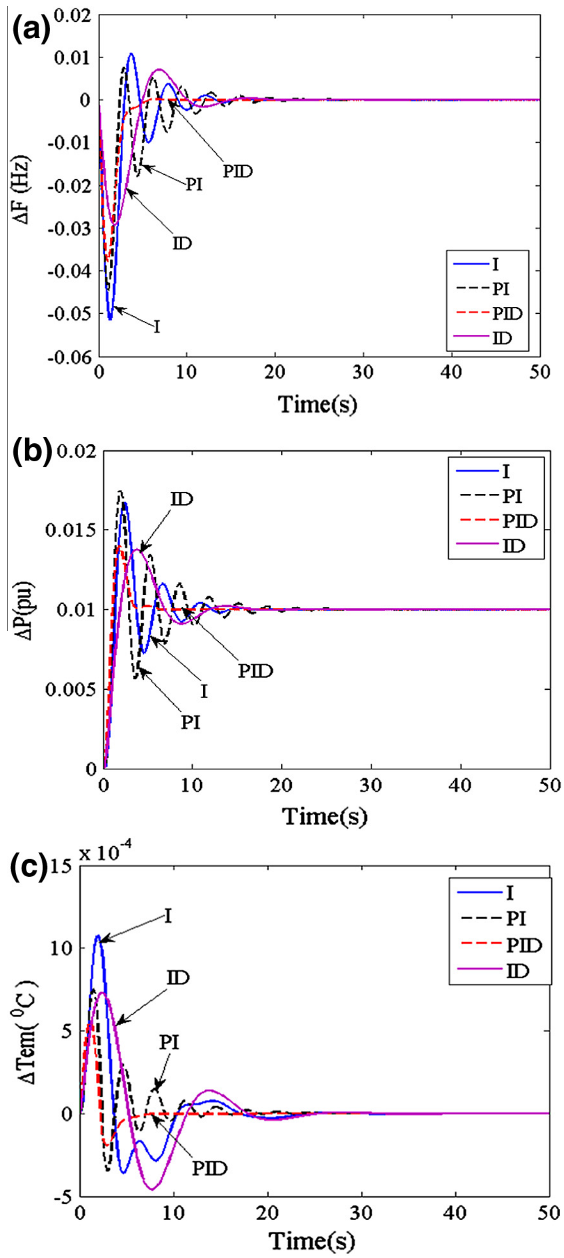

Fig. 4. Comparison of dynamic responses for different classical controllers. (a) Deviation of frequency vs. time, (b) deviation of power vs. time, and (c) deviation of exhaust temperature vs. time.

$$\Delta T_f = \Delta T_d + K_2 \frac{\Delta W_a}{W_{a0}} - K_2 \frac{W_{f0}}{W_{a0}^2} \Delta W_a \tag{9}$$

$$\Delta T_e = (1-\eta_T)\Delta T_f + \eta_T \frac{\Delta T_f}{x_0} - \eta_T \frac{T_{f\max}}{x_0^2} \Delta x \tag{10}$$

$$\Delta P_s = K_s(W_{a0}\Delta T_e + T_{eo}\Delta W_a) \tag{11}$$

$$\Delta P_g = K_g \Delta W_f \tag{12}$$

where subscript ‘0’ represents the steady state value of the variables. Per unit change in turbine exhaust temperature is given by

$$\Delta T_e(\mathrm{pu}) = \frac{\Delta T_e}{T_{e0}} \tag{13}$$

After combining the Eqs. (7)–(11), we can get the Eqs. (14) and (15)

$$\Delta T_e(\mathrm{pu}) = \alpha_{11}\Delta W_f + \alpha_{12}\Delta W_a \tag{14}$$

$$\Delta P_s(\mathrm{pu}) = \alpha_{21}\Delta W_f + \alpha_{22}\Delta W_a \tag{15}$$

where

$$\alpha_{11} = \left(1 - \eta_T + \frac{\eta_T}{x_0}\right)\frac{K_2}{W_{a0}}$$

$$\alpha_{12} = (P_{r0})^{1-\frac{1}{\gamma}}\left(1 - \frac{1}{\gamma}\right)\frac{1}{W_{a0}}\left[\left(1 - \eta_T + \frac{\eta_T}{x_0}\right)\frac{T_i}{\eta_c} - \frac{\eta_T}{x_0^2}T_{f0}\right] - \left(1 - \eta_T + \frac{\eta_T}{x_0}\right)\frac{K_2 W_{f0}}{W_{a0}}$$

$$\alpha_{21} = K_s W_{a0}\alpha_{11}$$

$$\alpha_{22} = K_s(T_{e0} + W_{a0}\alpha_{12})$$

The value of α_{11}, α_{12}, α_{21}, and α_{22} used in Eqs. (14) and (15) will have to calculate for modeling of gas turbine in small signal analysis. Here the nominal loading of off grid CCGT plant of 1000 MW is 80%, since CCGT generally operates between 70% and 100% of loading. In our model we consider a single-shaft combined cycle plant. Its rated power output is 1000 MW (gas turbine: 666.7 MW, steam turbine: 333.3 MW). Typical parameters are provided in the appendix A for the gas turbine and steam turbine. These typical parameters may change for practical turbines.

The small signal model of the CCGT plant is shown in Fig. 2. Most of the parameters used are same as used in models described in [1–3]. Plant model consists of three controllers

1. Secondary controller, which responds very fast as the frequency deviates from its nominal value, causing change in the fuel flow to maintain the balance between load and generation.
2. Temperature controller, which maintains the measured exhaust temperature to the level of reference temperature by controlling the fuel flow. It limits the fuel flow when the measured exhaust temperature exceeds the reference temperature.
3. Air flow controller, which controls the air flow in the compressor by variable inlet guide vanes fitted at the entrance of compressor. On increase in the fuel flow IGVs move from their minimum position to maximum position to maintain the reference exhaust gas temperature. At 100% loading IGVs are fully open and any increase in fuel flow, air flow cannot be increased by IGVs. IGVs are very fast responding but when the fuel flow changes too rapidly, the IGVs may not maintain the correct air to fuel ratio.

Table 2
Values of setting time, peak overshoot and peak undershoot of Fig. 4.

Controllers	Settling time (s)			Peak overshoot			Peak undershoot		
	Fig. 4a	Fig. 4b	Fig. 4c	Fig. 4a	Fig. 4b	Fig. 4c	Fig. 4a	Fig. 4b	Fig. 4c
I	20.67	17.82	25.76	0.01067	0.0169	0.00107	−0.0515	0.00736	−0.0004
PI	21.92	23.90	23.89	0.00703	0.01746	0.00074	−0.0444	0.00568	−0.0003
PID	6.396	7.751	7.262	0.00006	0.01399	0.00056	−0.0377	0.00999	−0.0002
ID	15.84	16.7	25.02	0.00703	0.01376	0.00073	−0.0293	0.00909	−0.0005

Table 3
Optimum values of PID gains at different loading conditions and inertia constants.

Gains	Loading						Inertia constant (H) = 5 s	
	+5%	−5%	+10%	−10%	+15%	−15%	+20%	−20%
K^*_{ITEMP}	0.0177	0.0823	0.0157	0.0398	0.0146	−0.0142	0.0300	0.0707
K^*_{IAIR}	5.9689	2.9260	5.2633	2.9198	2.7068	4.5391	7.3597	6.0976
K^*_{ISEC}	0.2004	0.2234	0.2114	0.1893	0.2072	0.2251	0.1916	0.2051
K^*_{PTEMP}	4.3365	3.7664	0.8763	6.9654	9.9876	5.4964	3.5383	1.5637
K^*_{PAIR}	6.9674	8.7247	5.7563	3.4196	9.5855	4.7404	9.4079	6.9579
K^*_{PSEC}	0.1375	0.1288	0.1564	0.1663	0.0796	0.1385	0.1578	0.1064
K^*_{DTEMP}	0.0291	0.0573	0.0505	0.0267	0.0595	0.0191	0.0390	0.0394
K^*_{DAIR}	0.0392	0.0726	0.0345	0.0791	0.0372	0.0457	0.1162	0.0890
K^*_{DSEC}	0.1455	0.1290	0.1105	0.1365	0.1425	0.1268	0.0782	0.1443

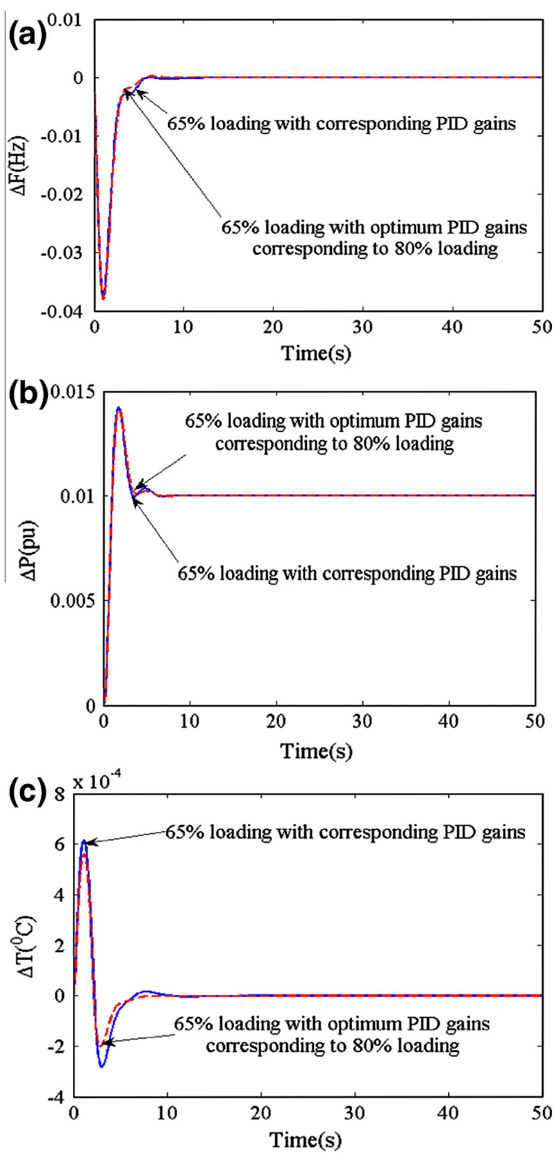

Fig. 5. Comparison of dynamic responses as a function of time for 65% loading with optimum PID gains corresponding to 65% loading and 80% loading. (a) Deviation in frequency, (b) deviation in power, and (c) deviation in temperature.

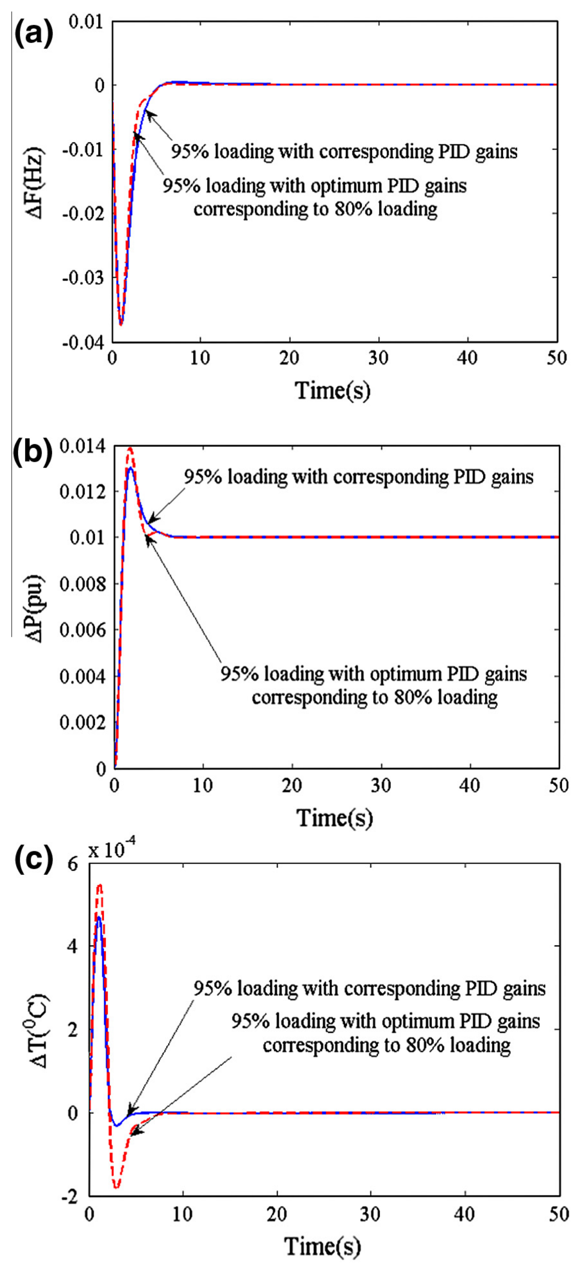

Fig. 6. Comparison of dynamic responses as a function of time for 95% loading with optimum PID gains corresponding to 95% loading and 80% loading. (a) Deviation in frequency, (b) deviation in power, and (c) deviation in temperature.

4. Firefly Algorithm

The Firefly Algorithm (FA) was induced by Yang [12,13]. The algorithm was based on the idealized behavior of the flashing characteristics of fireflies. The idealized flashing characteristics of the firefly is based on the following assumptions.

(a) All fireflies are unisex so that one firefly is attracted to other fireflies regardless of their sex.
(b) Attractiveness is proportional to their brightness. Thus for any two flashing fireflies, the less brighter one will move towards the brighter one. The attractiveness and brightness decrease as their distance increases. If no one is brighter than a particular firefly, it moves randomly.
(c) The brightness or light intensity of a firefly is affected or determined by the form of the objective function to be optimized. For a maximization problem, the brightness is proportional to the objective function. Other forms of brightness can be defined in a similar way to the fitness function in genetic algorithms or the bacterial foraging technique (BFT).

There are two issues in FA. They are variation of light intensity and formulation of the attractiveness. The attractiveness of a firefly is determined by its brightness or light intensity which in turn is associated with the objective function. For maximization problems, the brightness I of a firefly at a particular location x can be chosen as $I(x)/f(x)$. However, the attractiveness β is relative, it should be seen in the eyes of the beholder or judged by the other fireflies. Thus, it should vary with the distance r_{ij} between firefly i and firefly j. 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 the degree of absorption.

In the simplest form, the light intensity $I(r)$ varies with the distance r monotonically and exponentially.

That is

$$I = I_0 e^{-\gamma r} \tag{16}$$

where I_0 is the original light intensity and γ is the light absorption coefficient. As a firefly's attractiveness is proportional to the light intensity seen by adjacent fireflies, we can now define the attractiveness β of a firefly by

$$\beta = \beta_0 e^{-\gamma r^2} \tag{17}$$

where β_0 is the attractiveness at $r = 0$. It is worth pointing out that the exponent γr can be replaced by other functions such as γr^m when $m > 0$. Schematically, the Firefly Algorithm (FA) can be summarized as the pseudo code as follows.

$$\text{Objective function } f(x), x = (x_1, \ldots, x_d)^T \tag{18}$$

Initialize a population of fireflies x_i ($i = 1, 2, \ldots, n$).
Define light absorption coefficient γ

While (t < MaxGeneration)
  for $i = 1$: n all n fireflies
    for $j = 1$: i all n fireflies
      Light intensity I_i at x_i is determined by $f(x_i)$
      if ($I_j > I_i$)
      Move firefly i towards j in all d dimensions
      end if
      Attractiveness varies with distance r via exp $[-\gamma r^2]$
      Evaluate new solutions and update light intensity
    end for j
end for i
Rank the fireflies and find the current best
end while

Post process results and visualization.

The algorithm is used here for simultaneous optimization of different classical controllers. The cost function used here is the Integral Squired Error (ISE) given by the following equation:

$$J = \int_0^T [(\Delta F)^2 + (\Delta P)^2 + (\Delta T_{Tem})^2] dt \tag{19}$$

In this FA based optimization, the parameters of FA technique are tuned for optimal performance and their tuned values are number of firefly = 5, Maximum generation = 100, $\beta = 0.2$ $\alpha = 0.5$ and $\gamma = 0.5$.

5. Result and analysis

5.1. Performance comparison of different classical controllers

Several classical controllers like PI, I, PID, ID are used as secondary controller, air flow controller and the temperature controller. System dynamics are obtained by considering 1% step load perturbation (SLP). Each controllers are considered separately and the gains of the controllers are optimized separately using FA. Total nine variables (here PID controller gains of the secondary controller, temperature controller and air flow controller) are optimized successfully using this FA. To evaluate the merits of FA, the gains

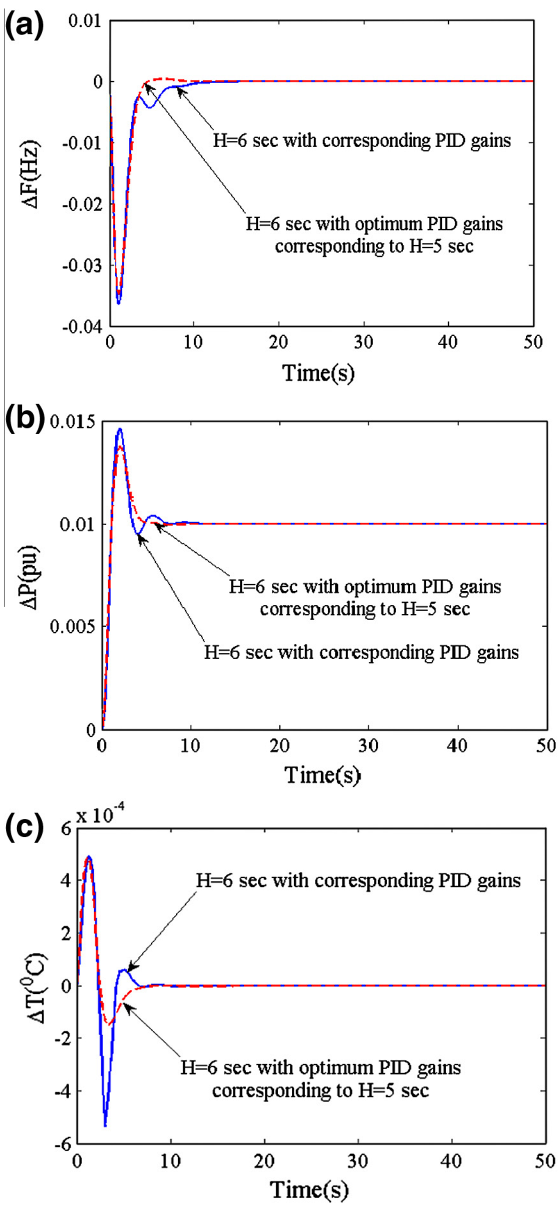

Fig. 7. Comparison of dynamic responses as a function of time for $H = 6$ s with optimum PID gains corresponding to $H = 6$ s and $H = 5$ s. (a) Deviation in frequency, (b) deviation in power, and (c) deviation in temperature.

are also optimized using BF technique and the convergence characteristics are obtained. The convergence characteristics of GA, PSO, BF, ABC and FA are compared and depicted in Fig. 3. It is clear that the FA converges faster than others. The obtained optimum values of I, PI, PID and ID controllers are shown in Table 1. Using these optimum gains, the dynamic responses for frequency, power and temperature are obtained and shown in Fig. 4a–c. Critical examination of the dynamic responses of Fig. 4, the values of overshoot, undershoot and settling time are noted and shown in Table 2. From these tables, it reveals that the responses corresponding to PID controllers are better than others from the point of view of magnitude of oscillations, peak deviations and settling time.

5.2. Sensitivity analysis

Sensitivity analysis is carried out to study the robustness of the optimum PID controllers gains K_P, K_I, and K_D obtained at nominal conditions to wide changes in the system loading condition by ±15% from its nominal loading of 80%, wide changes in system parameters such as inertia constant (H), by ±20% from their nominal value (5 s). The optimum values of PID controllers gains at changed loading conditions and changed system parameters (H) are shown in Table 3. Dynamic responses for each changed condition with their corresponding optimum PID gains and PID gains obtained at nominal condition are compared and shown in Figs. 5, 6, and 7a–c. Critical examination of frequency, exhaust temperature and generated power responses of Figs. 5–7 clearly reveals that responses are more or less same. Only nine dynamic responses in Figs. 5–7 are provided to justify the said statement. Thus, the optimum values of PID controllers (for air flow, temperature and secondary controllers) obtained at the nominal $H = 5$ s and nominal loading of 80% need not be reset for wide changes in the system loading or system parameter, H.

6. Conclusion

A simplified small signal model of CCGT plant has been developed to study its frequency regulation performances. Firefly Algorithm has been used for the first time in a small signal model of CCGT plant for optimization of controllers gains. Several classical controllers such as Integral (I), Proportional–Integral (PI), and Integral–Derivative (ID and Proportional–Integral–Derivative (PID) are used as air flow controller, temperature controller and secondary controllers in the CCGT model and their performances are compared. Studies reveal that FA optimized PID controller is the best over other controllers. Sensitivity analysis reveals that the optimum PID gains obtained at nominal condition of loading and inertia constants are robust and need not be reset for wide changes in the system loading or system parameter, H.

Appendix A

A.1. Nominal parameters of the system investigated

$T_{i0} = 30$ °C, $T_{d0} = 390$ °C, $T_{e0} = 532$ °C, $T_{f0} = 1085$ °C, $P_{r0} = 11.5$, $\gamma = 1.4$, $\eta_c = 0.85$, $\eta_T = 0.85$, $T_g = 0.05$, $T_3 = 15$ s, $T_4 = 2.5$ s, $K_4 = 0.8$, $K_5 = 0.2$, $K_3 = 3.3$, $K_6 = 25$, $T_v = 0.1$ s, $T_f = 0.4$ s, $T_{cd} = 0.2$ s, $T_m = 5$ s, $T_b = 20$ s, $T_{igv} = 0.05$ s, $K_g = 0.64$, $K_s = 0.00043$, $R = 2.4\%$, $D = 1\%$, $H = 5$ s, and Loading = 80%.

References

[1] Carmona S, Rios S, Pena H, Nakic G. Combined cycle unit controllers modification for improved primary frequency regulation. IEEE Trans Power Syst 2010;25(3):1648–54.
[2] Kakimoto N, Baba K. Performance of gas turbine-based plants during frequency drops. IEEE Trans Power Syst 2003;18(3):1110–5.
[3] Lalor G, Ritchie J, Flynn D, O'Malley MJ. The impact of combined-cycle gas turbine short-term dynamics on frequency control. IEEE Trans Power Syst 2005;20(3):1456–64.
[4] Saikia LC, Sinha N, Nanda J. Maiden application of bacterial foraging based fuzzy IDD controller in AGC of a multi-area hydrothermal system. Int J Electr Power Energy Syst 2013;45:98–106.
[5] Passino KM. Biomimicry of bacterial foraging for distributed optimization and control. Control Syst, IEEE 2002;22(3):52–67.
[6] Saikia LC, Nanda J, Mishra S. Performance comparison of several classical controllers in AGC for multi-area interconnected thermal system. Int J Electr Power Energy Syst 2011;33:394–401.
[7] Lin W, Liu PX. Hammerstein model identification based on bacterial foraging. Electron Lett 2006;42:1332–4.
[8] Golpîra H, Bevrani H. Application of GA optimization for automatic generation control design in an interconnected power system. Energy Convers Manage 2011;52:2247–55.
[9] Gozde H, Taplamacioglu MC. Automatic generation control application with craziness based particle swarm optimization in a thermal power system. Int J Electr Power Energy Syst 2011;33:8–16.
[10] Chaturvedi DK, Satsangi PS, Kalra PK. Load frequency control: a generalized neural network approach. Int J Electr Power Energy Syst 1999;21:405–15.
[11] Gozde H, Taplamacioglu MC, Kocaarslan I. Comparative performance analysis of artificial bee colony algorithm in automatic generation control for interconnected reheat thermal power system. Int J Electr Power Energy Syst 2012;42:167–78.
[12] Yang XS. Nature-inspired meta-heuristic algorithms. Beckington, UK: Luniver Press; 2008.
[13] Yang XS, Firefly algorithm for multimodal optimization, stochastic algorithms: foundations and applications. SAGA 2009, Lecture notes in computer sciences, vol. 5792. p. 169–78.
[14] Lukasik S, Zak S. Firefly algorithm for continuous constrained optimization task. In: Ngugen NT, Kowalczyk R, Chen SM, editors. ICCCI 2009, Lecture notes in artificial intelligence, vol. 5796; 2009. p. 97–100.
[15] Senthilnath J, Omkar SN, Mani V. Clustering using firefly algorithm: performance study. Swarm Evol Computat 2011;1:164–71.
[16] Yang XS, Hosseini SS, Gandomic AH. Firefly algorithm for solving non-convex economic dispatch problems with valve point loading effect. Appl Soft Computing 2012;12:1180–6.
[17] Rowen WI. Simplified mathematical representations of heavy-duty gas turbines. J Eng Power 1983;105(4):865–9.
[18] Rowen WI. Simplified mathematical representations of single-shaft gas turbines in mechanical drive service. Turbomach Int 1992(July–August):26–32.
[19] Ning CN, Lu CN. Effects of temperature control on combined cycle unit output response. In: IEEE Region 10 conference, TENCON 2006; 2006. p. 1–4.
[20] Zhang Q, So PL. Dynamic modeling of a combined cycle plant for power system stability studies. In: Power engineering society winter meeting, vol. 2; 2000. p. 1538–43.
[21] Yee SK, Hughes FM, Milanovic JV. Comparative analysis and reconciliation of gas turbine models for stability studies. In: Proc power eng soc general meeting, vol. 1; 2007. p. 1–8.
[22] Pourbeik P. Modeling of combined cycle power plants for power system studies. In: Proc power eng soc general meeting, vol. 3; 2003. p. 1308–13.
[23] Anderson P, Fouad A. Combustion turbine and combined cycle power plants, power system control and stability. 2nd ed. Portland, OR: Wiley; 2003. p. 513–28.