I J C T A, 9(16), 2016, pp. 8245-8255

Development of Optimal Controller for Large Signal and Small Signal Model of Gas Turbine Plant using Particle Swarm Optimisation

S. Selva Kumar*, Vignesh Venkiteswaran and R. Udhayaraj****

ABSTRACT

The gap between supply and demand in electrical power system is a serious problem faced by developing nations thriving towards economic supremacy. Alternative sources other than conventional non-renewables and distributed generation using renewable sources were looked into for overcoming energy crisis. With the advent of heavy duty gas turbine plants using biomass fuel in the distributed generation, it is impeccable to develop a suitable controller for the gas turbine plants operating in standalone and interconnected modes. Suitable large signal and small signal models for the gas turbine plants were considered and the secondary proportional + Integral (PI) controllers are tuned for the models using Ziegler Nichol's (ZN), Genetic algorithm (GA) and Particle Swarm Optimization (PSO) techniques. From transient and steady state analysis of the system it is found that PSO technique had provided optimal controller tuning for small and large signal models of gas turbine plants.

Keywords: Gas turbine model, PI controller, ZN, GA, PSO

1. INTRODUCTION

With depleting fossil fuels over the years, the need and usage of alternative using renewable sources is under limelight. As an evolution, the power system also had moved towards distributed generation and control. Heavy duty gas turbine plants fuelled by bio mass gasification units can be one of the better options when it comes to distributed generation. These gas turbine plants are highly sensitive to large load changes and may go to instability if not properly controlled. The stable, economic and reliable operation of heavy duty gas turbine plant depends on the control involved.

To analyse the system under different loading conditions, suitable gas turbine model is necessary. Rowen [1] proposed a large signal model using the coefficients and constants he derived on actual experimental results done on the gas turbine system. He proposed speed, acceleration and temperature based control of gas plant. Later, Balamurugan [2] had simplified that model with speed based control and with optimised selection of rotor constants and droop settings. He also developed soft computation based secondary controllers for that simplified model [3, 4]. For interconnected operation of gas turbine plant with other sources like thermal and hydro and to execute load frequency control small signal model was developed for gas turbine plant [5, 6]

The speed governor is the primary controller for gas turbine plants which may be a droop or of isochronous type. The droop governor is predominantly used type of speed governor characterised with drooping nature.

---

* Assistant Professor Senior Grade,

** Student Department of Electrical and Electronics Engineering Amrita School of Engineering, Coimbatore Amrita Vishwa Vidyapeetham, Amrita University, India

Hence, the response of the system will have constant steady state error. So a suitable secondary controller is required. The work explained in this paper aims to develop a suitable secondary controller for the large signal and small signal models of the gas turbine plant using PSO and compare the results with the ZN and GA tuned controllers.

2. MODELLING OF GAS TURBINE PLANT

The large signal model of the gas turbine plant is developed to understand and analyse the behaviour of the system to change in external load. Rowen's model is considered to be the best suited for this application as it is consistent and more adaptable to external factors. The large signal model of gas turbine plant is shown in Fig. 1 consisting of the speed governor that varies the fuel output depending on the change in load torque. The process variable to be controlled is the speed of the turbine.

The small signal model is used to demonstrate load frequency control and it is derived from the large signal model. The coefficients and constants implemented in the system are as per Rowen's model. The small signal model for the gas turbine plant used in this work is shown in Fig. 2. The process variable to be controlled in this model is change in frequency.

The system consists of the speed governor as the primary controller and a befittingly tuned secondary controller that control the change in frequency, Δf. Fine tuning of the system so as to bring Δf to zero is done with the help of the secondary control loop using a PI controller.

3. TUNING OF SECONDARY CONTROLLER

The secondary controller used in both large signal and small signal models is a PI controller involving gain constants K_p and K_i which is to be tuned suitably using ZN, GA and PSO techniques.

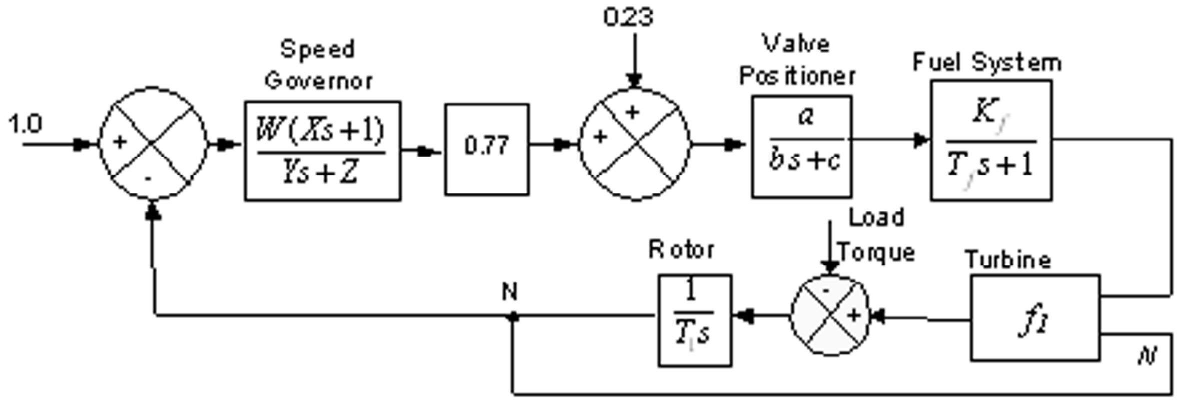

Figure 1: Large Signal Model of Gas Turbine Plant

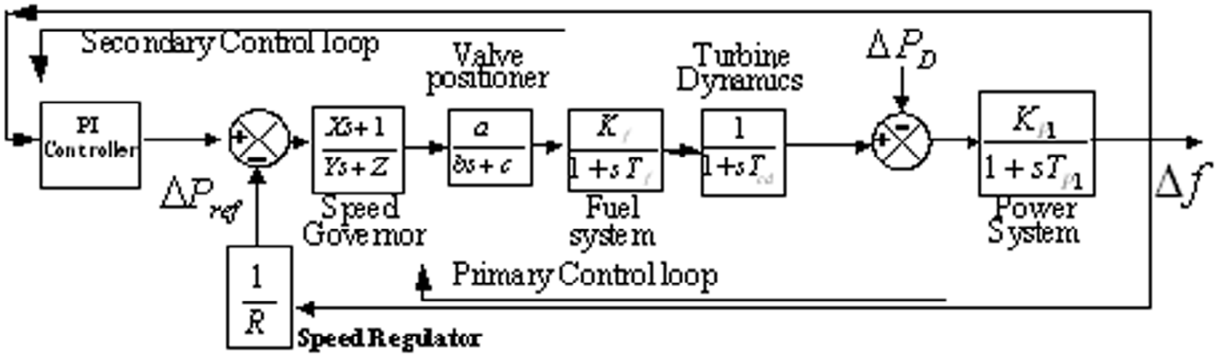

Figure 2: Small Signal Model of Gas Turbine Plant with Secondary Controller

3.1. Zeigler-Nichols' method

Zeigler-Nichols' [7, 8] method is a bench mark technique used to determine the gain constants of controllers. It involves the process of determining the ultimate gain, K_u and ultimate time period, T_u of the system by increasing the proportional gain in the control loop till sustained oscillations with constant amplitude and frequency is obtained for the process variable. From the values of K_u and T_u, the gain constants of PI controller namely K_p and K_i are calculated using Equations (1) and (2).

$$K_p = 0.45K_u \tag{1}$$

$$K_i = \frac{1.2K_p}{T_u} \tag{2}$$

The K_u and T_u values for large signal model were obtained as 5.575 and 1.35s respectively. Similarly for the small signal model they are 0.7151 and 1.8s. The calculated values of PI controller gains K_p and K_i are shown in Table 1.

Table 1
ZN Tuned PI Gains for Large and Small Signal Model

Model	K_p	K_i
Large Signal Model	2.508	2.322
Small Signal Model	0.3218	0.2145

3.2. Genetic Algorithm method

GA is a search algorithm that imbibes concepts of natural selection and genetic inheritance, to determine the most optimal solution from a population of potential solutions [9, 10]. It consists of a fitness function

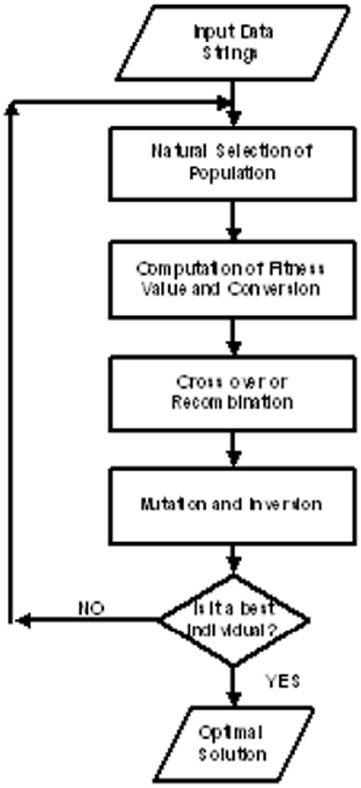

Figure 3: Genetic Algorithm Flow Chart

that is to be maximised or minimised to obtain an optimal solution. For the current application, the Integral Square Error (ISE) is taken as the fitness function to be minimised. The various genetic operations like cross over, mutation and inversion were done over the intial population to arrive at the optimal solution as per the flow chart shown in Fig. 3.

For the systems under study, the number of variables involved is 2 in each model. The intial population is taken as 10 with 20 bits of string length. GA is applied with cross over probability of 0.05 and mutation probability of 0.8 for tuning the PI gain constants. The search algorithm is executed till the best value and mean value of the fitness function are equal. The GA tuned PI gain constants for large and small signal models were shown in Table 2.

Table 2
GA Tuned PI Gains for Large Signal and Small Signal Model

Model	K_p	K_i
Large Signal Model	2.0683	0.3075
Small Signal Model	0.2862	0.2232

3.3. Particle Swarm Optimization Technique

The sole objective of optimization is to establish a solution that is unique, pertinent and the most appropriate under the given circumstances. Mathematically, any optimization problem consists of a fitness function that describes the predicament under certain boundary parameters and solution space. This is facilitated by the Particle Swarm Optimization technique [11], which is a multi-dimensional parallel search process providing successful solutions with minimum parameters.

The process is swift and the calculations involved do not involve any complications. In comparison to other developing calculations, PSO inhabits a greater optimization ability [12]. The algorithm of PSO has

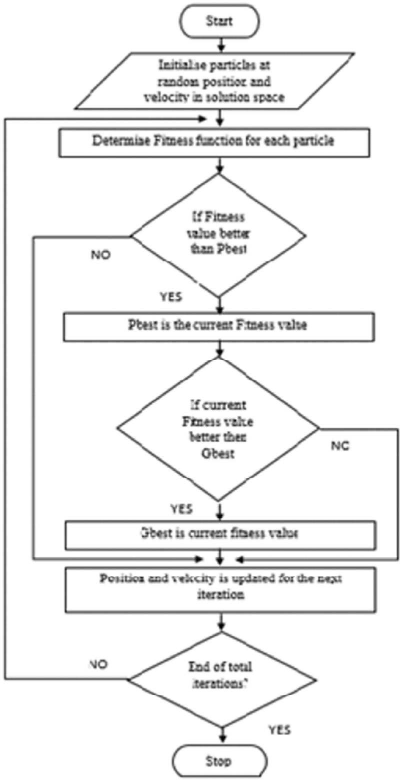

Figure 4: PSO algorithm flowchart.

been emulated from the general activities and conducts of animal civilizations that constitute the swarm such as bird flocking and fish schooling. Fig. 4 explains the basic flow of the processes involved.

The characteristic feature of every particle in a solution space is its velocity and position which is unique. The fitness function in this gas turbine system is the ISE which is the function to be minimised. With respect to the position of the particle for the given iteration, its personal best (pbest) position is determined. The best position or the most optimized solution obtained by any particle in the entire system is called the Global best or gbest [13]. The gbest value acquired at the end of the n-iteration process is said to be the best-suited solution. By applying the concept of PSO, the value of gain constants is obtained as shown in Table 3 for large and small signal models.

Table 3
PSO tuned PI gains for Large Signal and Small Signal Model

Model	K_p	K_i
Large Signal Model	1.72865	0.04925
Small Signal Model	0.2622	0.2163

4. SIMULATION RESULTS AND DISCUSSION

Both Large and Small Signal models are simulated using MATLAB-Simulink platform [14] and the corresponding results are analysed. The large signal model is given a unit step load at time 0s. For the small signal model, a step load of magnitude 0.01 is given at time 0s.

4.1. Without Secondary Controller

The large and small signal models are simulated as shown in Fig. 1 and Fig 2 with the coefficients and constants as mentioned in Appendix. The systems are loaded as specified above. Fig. 5 and Fig. 6 shows the responses of the large signal and small signal models without secondary controller.

From the graphical response shown in Fig. 5, it is observed that the speed of the machine settles at a value below 1 p.u. providing a constant steady state error in the process varible.

From Fig. 6, it can be noted that the system after the initial load disturbance, did not return back to nominal operating condition of zero frequency deviation and exhibiting constant steady state error. The primary controller in both the models was not able to bring the system back to initial operating conditions owing to the drooping nature of the speed governor in the system and thereby insisting the importance of the secondary controller for fine tuning the process variable.

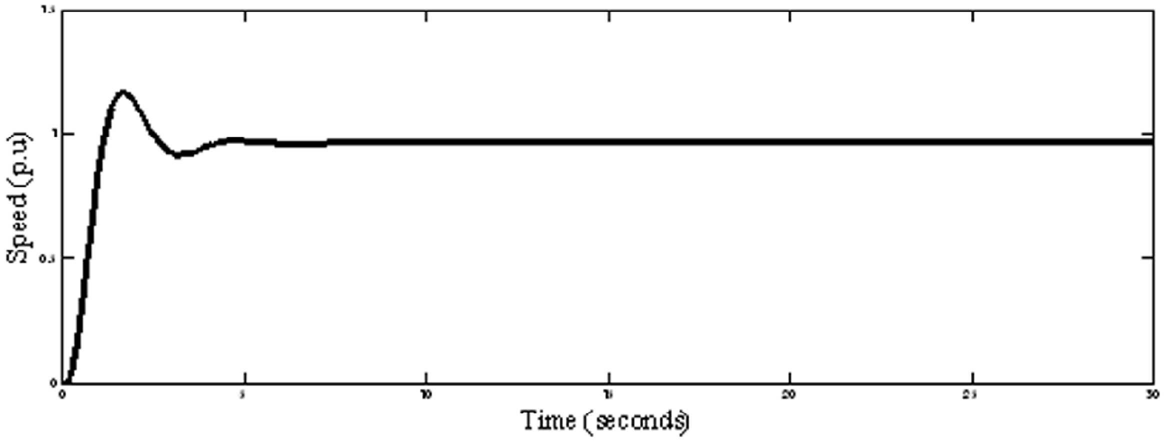

Figure 5: Response of Large Signal Model without Secondary controller

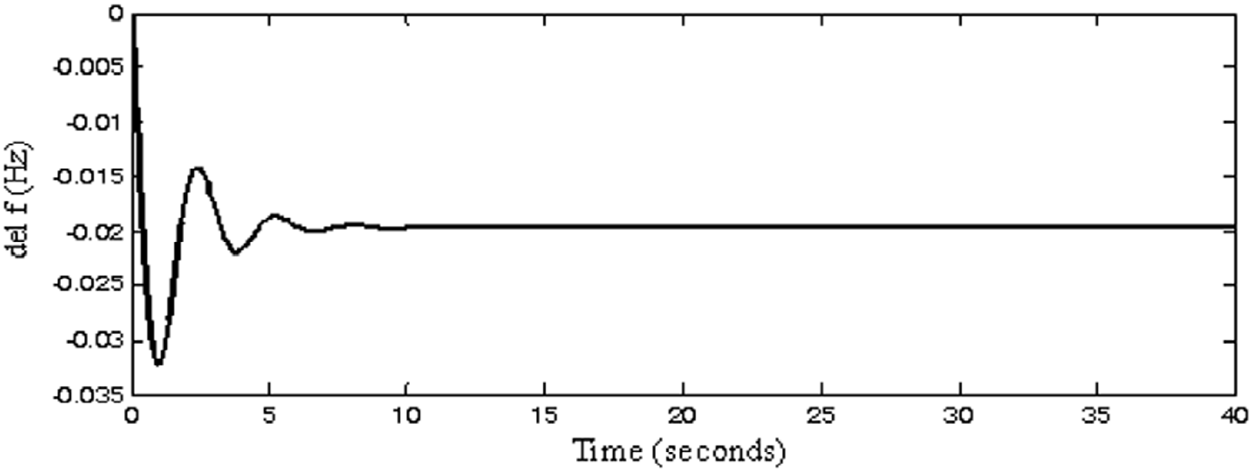

Figure 6: Response of Small Signal Model without Secondary controller

4.2. With Secondary Controller

4.2.1. ZN tuned controller

The large and small signal models are enhanced with ZN tuned secondary controller with the gain constants shown in Table 1. The systems were simulated with intial load conditions as discussed before and simulated. The time response for both models is shown in Fig. 7 and Fig. 8.

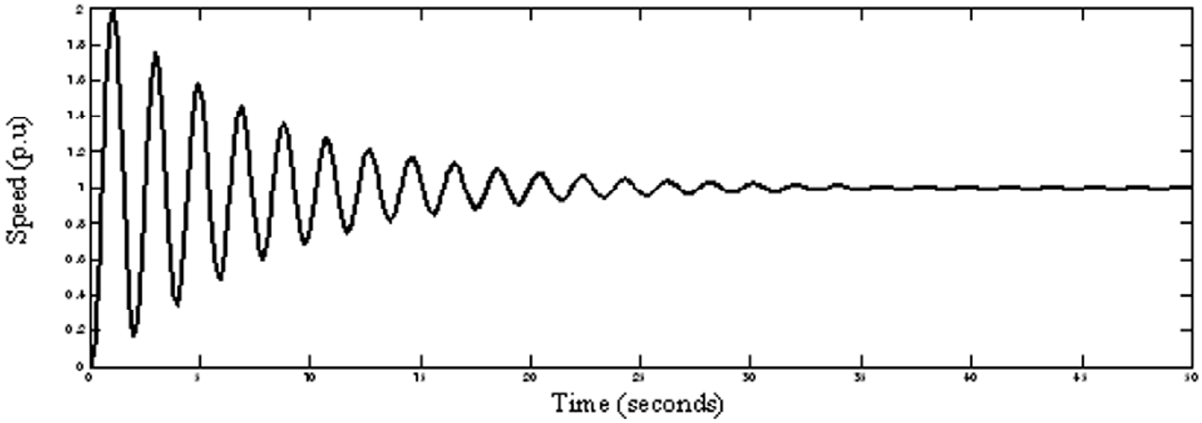

Figure 7: Response of Large Signal Model with ZN tuned PI Controller

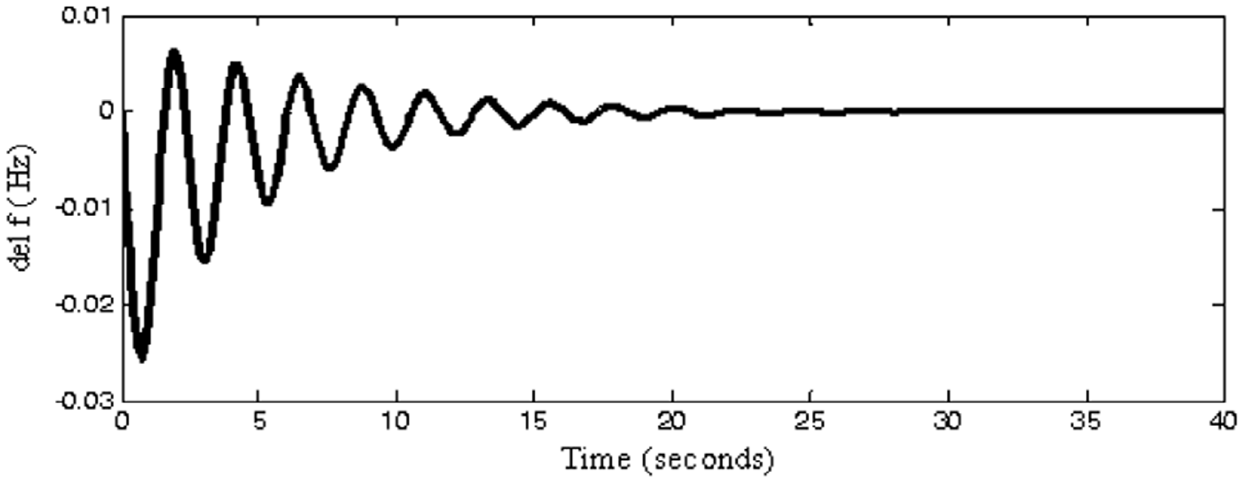

Figure 8: Response of Small Signal Model with ZN tuned PI Controller

The graphical responses indicate that both the systems had their process variables settled at their nominal operating conditions with zero steady state error. But the transient response is found to have large overshoots and prolonged settling time.

4.2.2. GA tuned controller

The gain constants mentioned in Table 2, as obtained by GA tuning is used for the PI controller gains and the system models were simulated for their responses with similar load disturbances as explained before. The responses are shown in Fig. 9 and Fig. 10.

From the responses it can be visualised that in both the models, the transient response had better features than ZN tuned systems and with zero steady state error.

4.2.3. PSO tuned controller

The large and small signal models are simulated with the PI controller gains shown in Table 3 obtained using PSO technique. The responses were illustrated in Fig. 11 and Fig.12.

PSO tuned controllers for the two systems had provided better control on process variables in both transient and steady state conditions. Graphical comparison is made for both the models with all the three tuning methadologies and illustrated in Fig. 13 and Fig. 14.

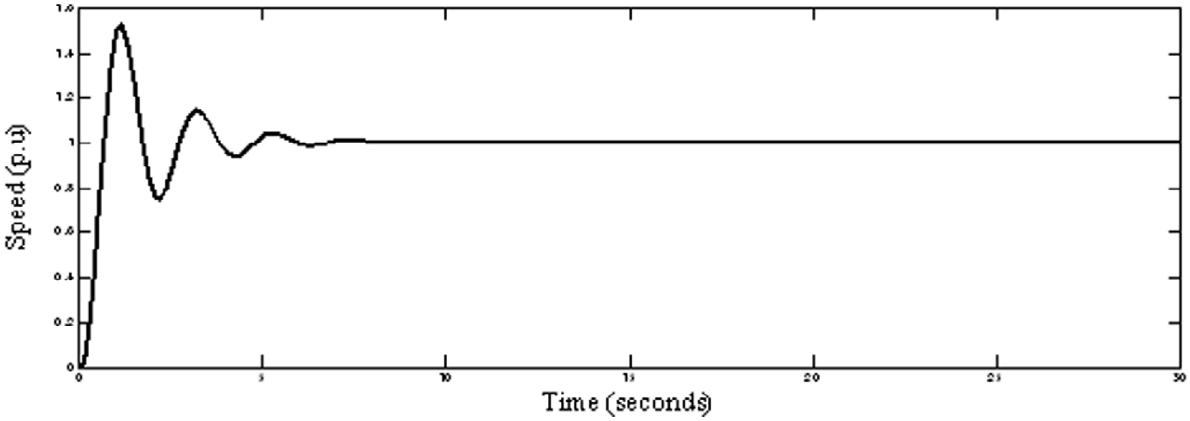

Figure 9: Response of Large Signal Model with GA tuned PI Controller

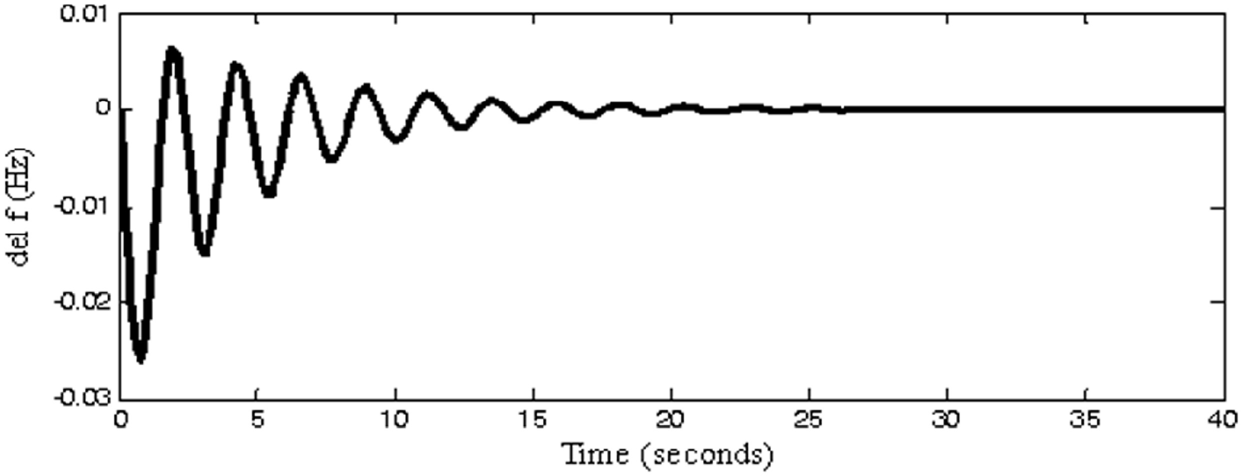

Figure 10: Response of Small Signal Model with GA tuned PI Controller

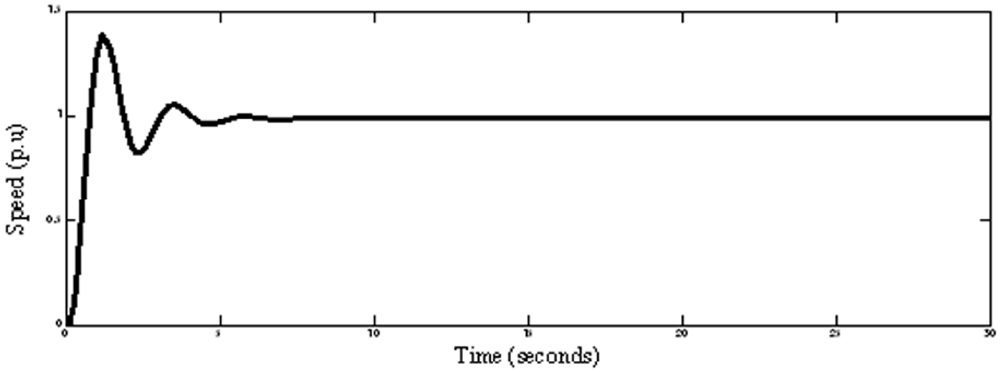

Figure 11: Response of Large Signal Model with PSO tuned PI Controller

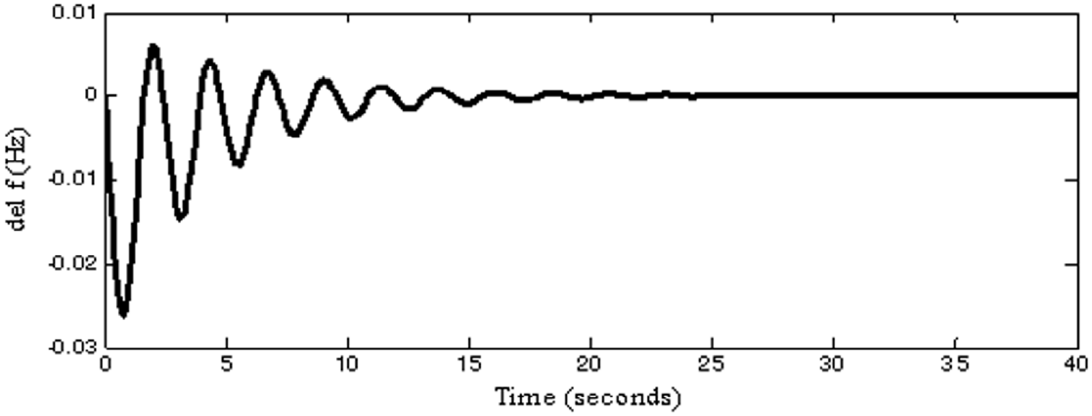

Figure 12: Response of Small Signal Model with PSO tuned PI Controller

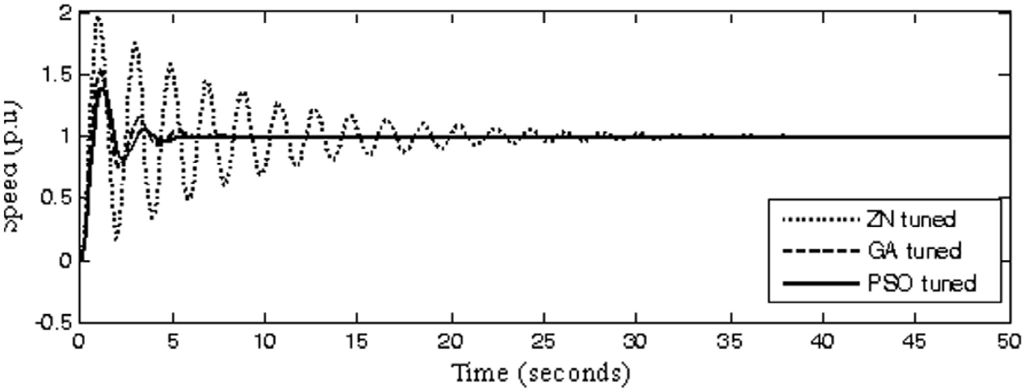

Figure 13: Comparison of Responses with ZN, GA and PSO tuned Controllers for Large Signal Model

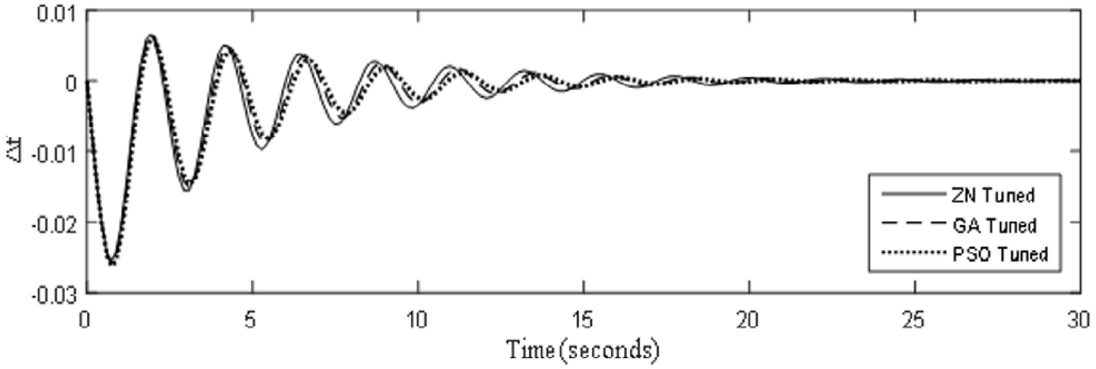

Figure 14: Comparison of Responses with ZN, GA and PSO tuned Controllers for Small Signal Model

The time domain specifications for both the models with different tuning methodologies are shown in Table 4 and Table 5.

Table 4
Comparison of Time Domain Analysis of Various Controllers for Large Signal Model

Controller Tuning	*Peak Overshoot (p.u)*	*Settling Time (s)*	*Steady State Error (p.u)*
ZN	2	45	0
GA	1.52	14	0
PSO	1.3864	7.88	0

Table 5
Comparison of Time Domain Analysis of Various Controllers for Small Signal Model

Controller Tuning	*Peak overshoot (p.u) [x 10^{-3}]*	*Settling time (s)*	*Steady State Error (p.u)*
ZN	6.52	92	0
GA	6.46	68	0
PSO	5.92	46	0

From the comparison of time domain specifications it proves that the PSO tuned systems had better values than the other two counterparts.

In addition to the time domain analysis, the performance indices [15] were calculated for the systems to provide a quantitative analysis on the performance of the different controllers on the system. Performance indices namely, Integral Squared Error (ISE), Integral Time Absolute Error (ITAE) and Integral Time Squared Error (ITSE) given by the Equations (3), (4) and (5) were measured from the system responses and shown in Table 6 and 7.

$$\mathrm{ISE} = \int \Delta f^2 \, \mathrm{dt} \tag{3}$$

$$\mathrm{ITAE} = \int t \, | \, \Delta f \, | \, \mathrm{dt} \tag{4}$$

$$\mathrm{ITSE} = \int t \, (\Delta f^2) \, \mathrm{dt} \tag{5}$$

Table 6
Comparison of Performance Indices of Various Controllers for Large Signal Model

Control Type	*ISE*	*ITAE*	*ITSE*
ZN	2.209	15.81	6.74
GA	0.5762	1.856	0.3975
PSO	0.5077	1.5	0.2574

Table 7
Comparison of Performance Indices of Various Controllers for Small Signal Model

Control Type	*ISE*	*ITAE*	*ITSE*
ZN	7.815	0.2135	0.0016
GA	7.77	0.1825	0.001395
PSO	7.71	0.161	0.00138

**Bold indicates the least performance index*

From the calculated values of the performance indices, the PSO tuned secondary controller showed least values for both small signal and large signal models of gas turbine plant.

6. CONCLUSION

The large signal and small signal models of heavy duty gas turbine plant were developed based on model proposed by Rowen. The models were promptly loaded and the responses are analysed without secondary controller. The importance of secondary controller is realised from the responses. Secondary PI controller is introduced in both the models with the gain constants of the controller tuned using ZN GA and PSO techniques. From the graphical responses, time domain analysis and values of performance indices, it is observed that the PSO tuned controller is a better controller for large signal and small signal model of heavy duty gas turbine plant.

APPENDIX

R	2 Hz/p.u.MW; Regulation of speed governor
K_{p1}	100; Power system gain constant
T_{p1}	20 s; Power system time constant
ΔP_{ref}	Change in reference power
Δf	Change in frequency
ΔP_D	Change in load increment
K_u	Ultimate gain of the system
T_u	Ultimate time period of the system
$\mathrm{K_p}$	Proportional gain constant
$\mathrm{K_i}$	Integral gain constant
X, Y & Z	$X = 0$; $Y = 0.05$; $Z = 1$; Speed Governor coefficients
a, b & c	$a = 1$; $b = 0.05$; $c = 1$; Fuel system coefficients
K_f	1; Fuel System gain constant
T_f	0.4; Fuel system time constant
f_1	turbine function in large signal model
T_{cd}	0.1; Compressor discharge volume time constant
s	Laplace operator
t	time in seconds

REFERENCES

[1] Rowen, W.I.:Simplified Mathematical Representation of Heavy Duty Gas Turbines. ASME J. of Engi for Pow. 105 (1983) 865-869

[2] Balamurugan, S, Xavier, R. J., Jeyakumar, A.E.:Selection of governor and optimization of its droop setting and rotor time constant for heavy duty gas turbine plants', Indian J. Pow. and Riv. Vall. Develop. 57(2007) 35–37

[3] Balamurugan, S, Xavier, R. J., Jeyakumar, A.E.: Fuzzy based controller for heavy duty gas turbine plant. J. of Elect. Engi., 8(2008) 61-66

[4] Balamurugan, S, Xavier, R. J., Jeyakumar, A.E.: ANN controller for heavy duty gas turbine plant," Int. J. of Appl. Engi. Res. 3(2008)

[5] Balamurugan, S., Janarthanan, N., Vijaya Chandrakala, K.R.M.: Small and large signal modeling of heavy duty gas turbine plant for load frequency control. Elsevier – Int. J. of Elec. Pow. and Ener.Sys. 79 (2016) 84–88

[6] Selva Kumar, S., Joseph Xavier, R., Balamurugan, S.:Small Signal Modelling of Gas Turbine Plant for Load Frequency Control. Biennial Int. Conf. on Pow. and Ener. Sys. (2016), Bengaluru, India.

[7] Ziegler, J. G., Nichols, N. B.: Optimum setting for automatic controllers. Trans. ASME, 64(1942) 759–768

[8] Astrom, K. J., Hagglund, T. :PID Controllers, Theory, Design and Tuning. 2nd Edition, Instrument Society of America

[9] Goldberg, D.E. :Genetic Algorithms in Search, Optimization and Machine Learning. Addison Wesley Longman (1989)

[10] Balamurugan, S., Xavier, R. J., and Jeyakumar, A. E.: Application of genetic algorithm in optimal PID gain tuning for heavy duty gas turbine plant. J. of Elect. Syst., 4(2008) 33

[11] Eberhart, R, Shi, Y. : Particle swarm optimization: developments, applications and resources. Proceedings of the 2001 Congress on Evolutionary Computation, 1(2001) 81 -86

[12] Gaing, Z.L:A Particle Swarm Optimization Approach For Optimum Design of PID Controller", IEEE Trans. on Ener. Conv., 19(2004) No.2 384-391

[13] Gonçalo Pereira:Particle swarm optimization. Artificial life by example, *ist.utl.pt*, Oct.3, 2010. [Online]. Available http://web.ist.utl.pt/gdgp/VA/pso.pdf. [Accessed: Oct. 3, 2003]

[14] The MathWorks Inc., MATLAB User Manuals, Natick, MA: The MathWorks Inc., (2000)

[15] Gopal, M., Control Systems Principles and Design, 2nd ed., India: Tata McGraw Hill, (2002)