A Dynamic Firefly Algorithm-Based Fractional Order Fuzzy-PID Approach for the Control of a Heavy-Duty Gas Turbine

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Abstract: Heavy duty gas turbines have long played an important role in energy production. Advanced turbine designs are expected to be highly efficient, able to quickly ramp the output power up and down and promptly tolerate loading variations without breaching emissions regulations. Control design plays an important role in ensuring high efficiency and performance of gas turbines. This paper proposes a fractional order fuzzy-PID approach for a heavy-duty gas turbine. The controller gains are optimized using a Firefly algorithm enhanced with a dynamic parameter selection. This latter is used to speed up the convergence rate of the Firefly algorithm, optimize the gains of the fractional order fuzzy-PID and enhance the performance and efficiency of the gas turbine. The proposed approach is implemented to the speed loop of a gas turbine in order to maintain the output temperature and the turbine's speed within their desired values during either a sudden change in loading or a drop in frequency. A comparison analysis with a standard Firefly algorithm-based approach was carried out to further assess the performance of the proposed evolved firefly algorithm-based approach.

Keywords: Heavy-duty gas turbine, Speed control, Fuzzy Fractional order, Dynamic firefly algorithm

1. INTRODUCTION

Though renewable energy sources have made huge strides over the past decade, grid integration challenges such as intermittency, lack of synchronous inertia, frequency and voltage interruptions are primary factors contributing to the continuous use of traditional power generation technologies (GlobalData (2018)).

Gas turbines are one of the main elements of combined cycle power plants (CCPP) for electric power generation (Forbes (2018)). They owe their popularity to the high power-to-weight ratio, ability to operate during peak power demand, flexibility and low cost compared to steam turbines (MKT (2018)). Accurate modeling, parameters estimation, and frequency (speed) and output voltage stabilization in the presence of load variations are key factors in the efficient operation and performance of gas turbines (Haji Haji et al. (2019a)).

Various controllers are proposed by researchers to keep the turbine speed at a desired level against the plant uncertainty and external disturbance. A PID controller is presented for the governor gas turbine system in Zhang (2000). However, the proposed controller's performance is highly dependent upon gain tuning, which is performed via trial and error. In Haji Haji et al. (2017) a fractional order fuzz-PID controller is implemented to control the speed output of a CCPP within an appropriate interval under uncertainties and output disturbances. A neuro-fuzzy controller is presented for a gas turbine plant in Jurado et al. (2002). The authors use a neural network to tune the fuzzy logic controller gains. The dynamic behavior and efficiency of a gas turbine plant during frequency drops are considered in Kakimoto and Baba (2003).

Most recently, it was shown that the use of fractional calculus for control and modeling combined with swarm intelligence (SI) and evolutionary algorithms, including particle swarm optimization (PSO), genetic algorithm (GA), and differential evolution (DE), enhances the efficiency of the classical controllers. Among the swarm-based approaches, the Firefly algorithm (FA) has shown excellence performance in solving various complex optimization problems. Yang et al. (2011) used FA to provide an optimal solution for economic dispatch problems. Senthilnath et al. (2011) applies FA for clustering problems. That paper uses standard benchmark functions and compares the effectiveness and performance of proposed FA with ABC and PSO algorithms. In Haji Haji and Monje (2018a), the dynamic selection approach was used to enhance the convergence rate and final optimization value of the FA algorithm. In that paper, authors clearly show the superiority of DFA compared to other state of the arts algorithms.

This paper proposes a Dynamic FA (DFA)-based fractional order fuzzy-PID (fuzzy-FOPID) controller for the speed loop of a gas turbine unit. The main contributions of this paper are as follows:

- A fractional order fuzzy-PID approach that is able to maintain the turbine's speed and exhaust gas temperature within their desired values under load demand disturbances.
- An enhanced Firefly algorithm with dynamic parameter selection to quickly auto-tune and optimize the controller gains.
- A highly efficient design that can promptly mitigate sudden frequency drops.

The remainder of the paper is organized as follows. The dynamic model of the gas turbine is briefly described in section II. The proposed DFA-based fractional order fuzzy-PID approach is described in Section III. The performance of the controller is assessed in Section IV. Comparison analysis to a classical FA-based fractional order PID approach is also carried over in this section. Conclusions are finally drawn in Section V.

2. GAS TURBINE MODEL

The block diagram for a single-shaft gas turbine plant is depicted in Figure 1. This latter is mainly comprised of a compressor, a turbine, and a combustion chamber. Using the Rowen's simplified model, the exhaust temperature T_X and the generated turbine torque T_{tr} can be expressed as follows (Rowen (1983)):

$$T_X = f_1 = 550(1 - N) + T_R - 700(1 - W_F), \quad (1)$$

$$T_{tr} = f_2 = 0.5(1 - N) + 1.3(W_F - 0.23), \quad (2)$$

where T_R is the turbine rated exhaust temperature, W_F denotes the per unit (pu) fuel flow, and N is the turbine rotor speed (pu). The model of the gas turbine includes the acceleration, temperature, and speed control loops. The speed control loop, which is the aim of this study, changes the fuel flow to compensate for any output frequency deviation. The temperature control loop acts through the fuel supply to prevent the turbine's overloading and severe overheating. The acceleration control loop is activated during the gas turbine's startup to reduce fuel flow and limit the rate of the shaft acceleration. The system parameters are illustrated in table A.1 (Rowen (1983); Mansouri Mansourabad et al. (2013)).

3. DFA-BASED FRACTIONAL ORDER FUZZY-PID CONTROLLER

Fractional calculus provides more flexibility in the design of the controllers and enhance the system control performance. Riemann-Liouville (Equation 3) and Caputo (Equation 4) are two main definitions that are widely used in literature (Efe (2011)).

$$D_y^\alpha = y^{(\alpha)} := \frac{1}{\Gamma(q-\alpha)}(\frac{d}{dt})^q \int_0^t \frac{y(\xi)}{(t-\xi)^{\alpha+1-q}} d\xi, \quad (3)$$

$$D_y^\alpha = y^{(\alpha)} := \frac{1}{\Gamma(q-\alpha)} \int_0^t \frac{y^q(\xi)}{(t-\xi)^{\alpha+1-q}} d\xi, \quad (4)$$

Table 1. Control Rules.

$\frac{d^\mu e}{dt^\mu}$ \ e	**N**B	**N**M	**N**S	**Z**O	**P**S	**P**M	**P**B
PB	ZO	PS	PM	PM	PB	PB	PB
PM	ZS	ZO	PS	PS	PM	PB	PB
PS	NM	NS	ZO	PS	PM	PM	PB
ZO	NM	NM	NS	ZO	PS	PS	PM
NS	NB	NM	NM	NS	ZO	PS	PM
NM	NB	NB	NM	NS	NS	ZO	PS
NB	NB	NB	NB	NM	NM	NS	ZO

where

$$\Gamma(x) = \int_0^\infty y^{x-1} e^{-y} dy \quad (5)$$

is the Gamma function, t is upper limit, $D := (d/dt)$, $\alpha \in \Re$, and q is an integer $(q - 1 \leq \alpha < q)$.

The fractional order PID or $PI^\lambda D^\mu$ (FOPID) extends the conventional PID controller, whose integral order λ and derivative order μ are not integer (Podlubny (1999)). The relationship between the control output $u(t)$ and the error signal $e(t)$ for the FOPID controller is described as:

$$u(t) = K_P e(t) + K_I D^{-\lambda} e(t) + K_D D^\mu e(t), \quad (6)$$

where K_D, K_I and K_P denote the derivative, integral and proportional gains, respectively, and $\lambda, \mu > 0$ are the fractional orders.

Using the above control framework, we propose the fuzzy-FOPID control scheme illustrated in Fig. 2. Here $r(t)$ is the speed reference, $u(t)$ is the control input and $y(t)$ is the rotor speed. The fuzzy-FOPID control scheme is a combination of a fuzzy PI and fuzzy PD controller, which are respectively the input and output to the fuzzy logic controller (FLC). Where K_d and K_e are the derivative and proportional gains of the PD controller and K_β and K_α are the integral and proportional gains of the PI controller. The best values for the control gains K_e, K_d, K_α, K_β, along with the integral and derivative orders λ, and μ are determined using the proposed DFA, which will be detailed in section 4.1.

The output of the fuzzy logic controller (FLC) is fuel flow and the inputs are the turbine speed deviation and its derivative. The fuzzy rules for the proposed fuzzy-FOPID speed controller are illustrated in table 1, where NB, NM, NS, ZO, PS, PM, PB are the fuzzy linguistic values and refer to negative big, negative medium, negative small, zero, positive small, positive medium, and positive big, respectively. The FLC output and error inputs membership functions are illustrated in Fig. 3.

4. FIREFLY ALGORITHM

FA is a swarm-based algorithm inspired by the flashing behavior of fireflies (Yang et al. (2011)). A simplified pseudo code of the FA is provided in Fig. 4. The attractiveness β of fireflies as a function of the distance r can be computed by the following generalized equation (Haji Haji and Monje (2018a); Yang et al. (2011)):

$$\beta(r) = \beta_0 e^{-\gamma r^2}, \quad (7)$$

where γ refers to the fixed light absorption coefficient, and β_0 is the attractiveness at $r = 0$. The Euclidian distance

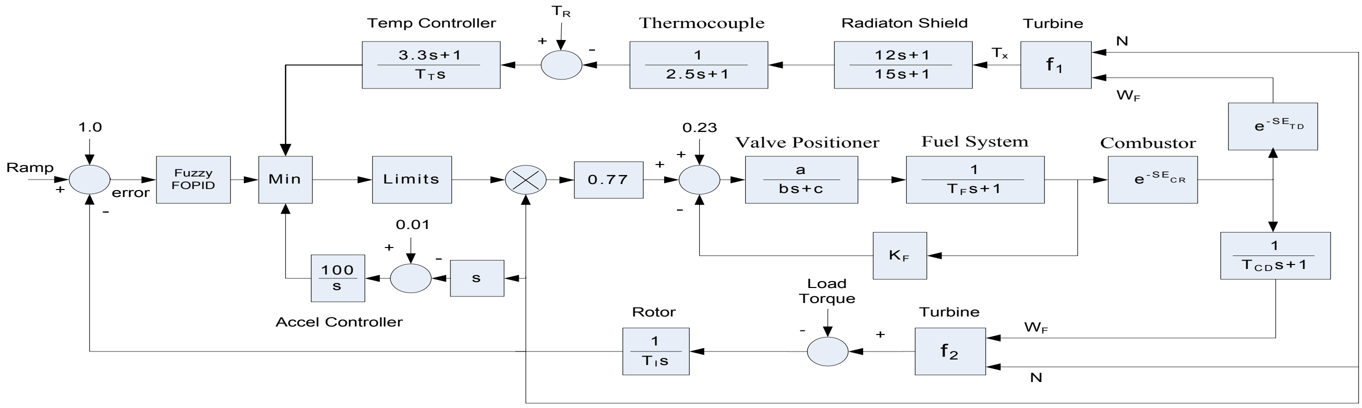

Fig. 1. Dynamic model of a gas turbine

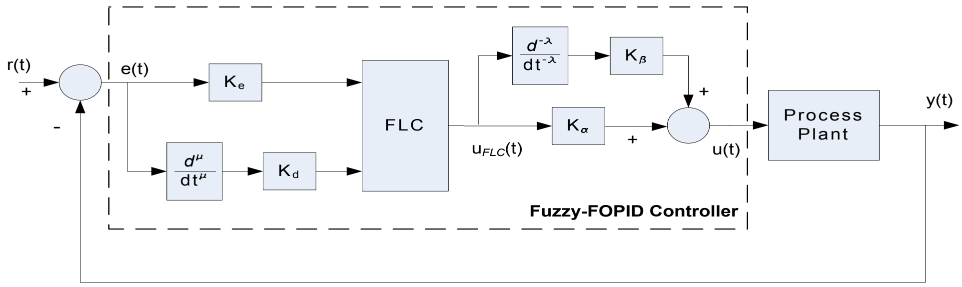

Fig. 2. Simplified block diagram of a fractional order fuzzy-PID controller.

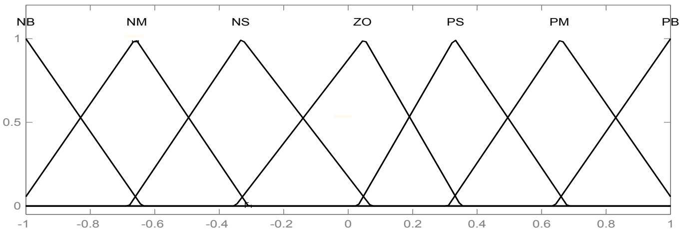

Fig. 3. Membership functions for FLC output, rate of error, and error.

Firefly Algorithm

Define γ, β_0, and α
Cost function $f(x), x = (x_1, ..., x_d)^T$
Generate random fireflies $x_i (i = 1, 2, .., n)$
Determine light intensity I_i *at* x_i *by* $f(x_i)$
While $(t < Maximum - Generation)$
  For $i = 1 : n$
    For $j = 1 : n$
      If $(I_j > I_i)$
      Move firefly i *towards* j based on the (9)
      EndIf
      Attractiveness varies with distance r *via* $exp[-\gamma r^2]$
      Evaluate new solutions and update light intensity
    EndFor j
  EndFor i
Rank all fireflies and choose the best one
EndWhile

Fig. 4. Pseudo code of the conventional firefly algorithm.

among i^{th} and j^{th} fireflies at location x_i and x_j is (Yang et al. (2011)):

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2}, \tag{8}$$

where $x_{i,k}$ and $x_{j,k}$ represent two different fireflies and d is the problem dimension. The movement of the fireflies is determined by Yang et al. (2011):

$$x_i = x_i + \alpha(rand - 0.5) + \beta_0 e^{-\gamma r_{ij}^2}(x_j - x_i), \tag{9}$$

where α denotes the step size scaling factor and $rand$ refers to a random number in the range of $[0, 1]$.

4.1 Dynamic Firefly Algorithm

In a typical algorithm, the control parameters play an essential role to solve the optimization problem.

In this work, a dynamic process is used to offer the best combination of PS, α, β_0, and γ in a firefly optimization problem. The simplified pseudo code of the DFA is shown in Fig. 5 (Haji Haji and Monje (2018a)). The DFA starts with a random population size $PS \in PS_{set} = \{PS_1, PS_2, ..., PS_{nps}\}$ (PS_i is assumed to be larger than PS_{i-1}) and a random combination of $\alpha \in \alpha_{set} = \{\alpha_1, \alpha_2, ..., \alpha_{n\alpha}\}$, $\beta_0 \in \beta_{0,set} = \{\beta_{0,1}, \beta_{0,2}, ..., \beta_{0,n\beta_0}\}$, and $\gamma \in \gamma_{set} = \{\gamma_1, \gamma_2, ..., \gamma_{n\gamma}\}$ for each individual in the population, where nps, $n\gamma$, $n\beta_0$, and $n\alpha$ are the cardinality of the set PS, γ, β_0, α, respectively. Based on the success rate SR and for a fixed number of generations (CS), the best combinations are used for the next generations. This procedure is called a cycle. The fireflies move by the following equation:

$$x_i = x_i + \beta_{0,i} e^{-\gamma_i r_{ij}^2}(x_j - x_i) + \alpha_i(rand - 0.5). \quad (10)$$

It is noticeable that the success rate of the combination SR_y is increased as $SR_y = SR_y + 1$ only if the firefly's new position x_i is better than its last position. Here, y is a selected combination of parameters, $y \in y_{set}$, and y_{set} includes all combinations of α_{set}, $\beta_{0,set}$, and γ_{set}. The population size of fireflies reduces to PS_{nps-1} and the remained individuals are archived after CS generations. The ranking of each combination is calculated as follows:

$$Rank_y = \frac{SR_y}{\text{the times that a combination } y \text{ is used}}. \quad (11)$$

Based on (8) the total number of combinations (TC) of y_{set} are divided to the half and combinations with higher $Rank_y$ are used for the next generations. After $CS \times nps$, based on (9) the best size of population is selected from PS_{set} and used for $(\eta - nps) \times CS$ next generations, while η is given by (10).

$$Rank_{PS_i} = \frac{\sum_1^{CS} \sum_{k=1}^{TC} SR_y}{PS_k^2}, \quad (12)$$

$$\eta \approx \frac{log(TC)}{log(2)}. \quad (13)$$

After $\eta \times CS$ iteration, the procedure starts over again with all possible combinations in y_{set}.

5. SIMULATION RESULTS

In this section, we implement the proposed fuzzy-FOPID in the speed control loop of the gas turbine. For comparison purposes, we tuned the controller gains using the FA and DFA algorithms. The DFA parameters are: maximum iterations = 70, $CS = 30$, $\eta = 3$, $PS \in \{5, 10\}$, $\alpha \in \{0.1, 0.3, 0.5, 0.7, 1\}$, $\beta_0 \in \{0.8, 1\}$, and $\gamma \in \{0.1, 1, 10\}$. Similarly, the tuning parameter of FA are: $PS = 10$, $\beta_0 = 1$, $\alpha = 0.9$, and $\gamma = 1$.

The well-known integral time squared error (ITAE) and integral time absolute error (ITSE) cost functions are considered to evaluate the superiority of the presented DFA-based controller compared to the controllers obtained using conventional FA algorithm. The gains of the speed controller are obtained using the time indices ITSE and ITAE as:

$$J_1 = ITSE = \int_0^\infty t.(ES^2(t) + t.EP^2(t))dt, \quad (14)$$

$$J_2 = ITAE = \int_0^\infty t.(|ES(t)| + t.|EP(t)|)dt, \quad (15)$$

where ES and EP are the speed and power error signals, respectively. The optimum gains and time indices parameters of the proposed factional fuzzy-PID controller using different algorithms are shown in table 2 and table 3, respectively. Figure 6 depicts the convergence rate of the FA and DFA algorithms for ITAE and ITSE errors. The best, worst, and average simulation results obtained in 10 runs are presented in table 4. As table 4 shows, the DFA can improve FA in order to offer the best average of cost function. For ITSE, Fig. 6 shows that the FA algorithm provides a fast convergence, but not faster than the DFA. From table 4 and Fig. 6, for ITAE, it is evident that the DFA offers a very low cost function.

Dynamic firefly algorithm

Define $i_{pop} = nps, \alpha_{set}, \beta_{0,set}, \gamma_{set}$, and PS_{set}
Cost function $f(x), x = (x_1, ..., x_d)^T$
Determine population of fireflies $x_i (i = 1, 2, .., n)$
Determine Light intensity I_i at x_i using $f(x_i)$
While $(t < Maximum - Generation)$
Assign a random combination from y_{set}
  For $i = 1 : n$ *fireflies*
    For $j = 1 : n$ *fireflies*
      If $(I_j > I_i)$
      Move firefly i towards j
      If new vector is better, then $SR_y = SR_y + 1$;**EndIf**
      EndIf
    EndFor j
  EndFor i
$period = period + 1;$
$PS_{prd} = PS_{prd} + 1;$
Rank each Firefly and find the best
If $period < (\eta * CS)$ *and* $mod(period, CS) = 0$
  Select the best half combination and update y_{set}
ElseIf $mod(period, \eta * CS) = 0$
  Set each $period = 0$ *and* $SR_y = 0$
EndIf
If $mod(PS_{prd}, CS) = 0$ *and* $i_{pop} > 0$
  Calculate $Rank_{PS_{i_{pop}}}$ *using (12)*
  set $i_{pop} = i_{pop} - 1$
    If $i_{pop} \sim= 0$
      Archive the worst $(PS_{i_{pop}+1} - PS_{i_{pop}})$ *individuals*
      Set $PS = PS_{i_{pop}}$
    EndIf
end If
If $PS_{prd} = nps * CS$ *and* $i_{pop} = 0$
  Set PS to the best population size
  Use necessary fireflies from the archive
EndIf
If $PS_{prd} = \eta * CS$
  Set $PS = PS_{i_{pop}}$, $i_{pop} = nps$, *and* $PS_{prd} = 0$
  Use necessary fireflies from the archive
  Clear all fireflies from the archive
EndIf
EndWhile

Fig. 5. Pseudo code of the dynamic firefly algorithm.

The dynamic power responses against load variations from 0.8 to 0.95 for the gas turbine controlled with the fractional fuzzy-PID controllers based on ITSE and ITAE cost functions are shown in Fig. 7. Based on the table 3 and Fig. 7, for the ITSE, the fuzzy-FOPID tuned by DFA algorithm offers a very low overshoot whereas the settling time and rise time are bigger than those with the FA algorithm. In terms of ITAE function minimization, Fig. 7 and table 3 show that the fractional fuzzy-PID-based FA algorithm provides a lower overshoot compared with the DFA algorithm.

Figure 8 provides the speed deviations of the gas turbine model based on the objective functions of ITAE and ITSE for both the FA and DFA algorithms. Note that in the case of ITSE, the DFA algorithm offers a lower final error and deviation than the FA algorithm, whereas this latter shows a lower final error in the case of ITAE error. From the results analysis, both FOPID controllers are able to bring back the speed into an appropriate level within a minimum

Table 2. Optimized FOPID gains determined using different algorithms.

Algorithms	K_e	K_β	K_d	λ	μ	K_α
$J_1 = ITSE$						
FA	7.6024	0.0049	7.99	0.729	0.011	3.3885
DFA	7.455	0.0074	7.991	0.6893	0.012	3.3548
$J_2 = ITAE$						
FA	7.992	0.0099	7.989	0.5291	0.013	3.2978
DFA	7.4882	0.0064	7.991	0.6895	0.011	3.4262

Table 3. Obtained objective function and time indices parameters using different algorithms.

Algorithms	Overshoot(%)	Rise Time(sec)	Settling Time(sec)	Objective Function
$J_1 = ITSE$				
FA	64.8084	0.4322	7.9675	2.8182
DFA	60.7037	0.4533	8.0153	2.8077
$J_2 = ITAE$				
FA	65.0955	0.4311	7.9549	130.8322
DFA	67.3275	0.4214	7.9437	130.3823

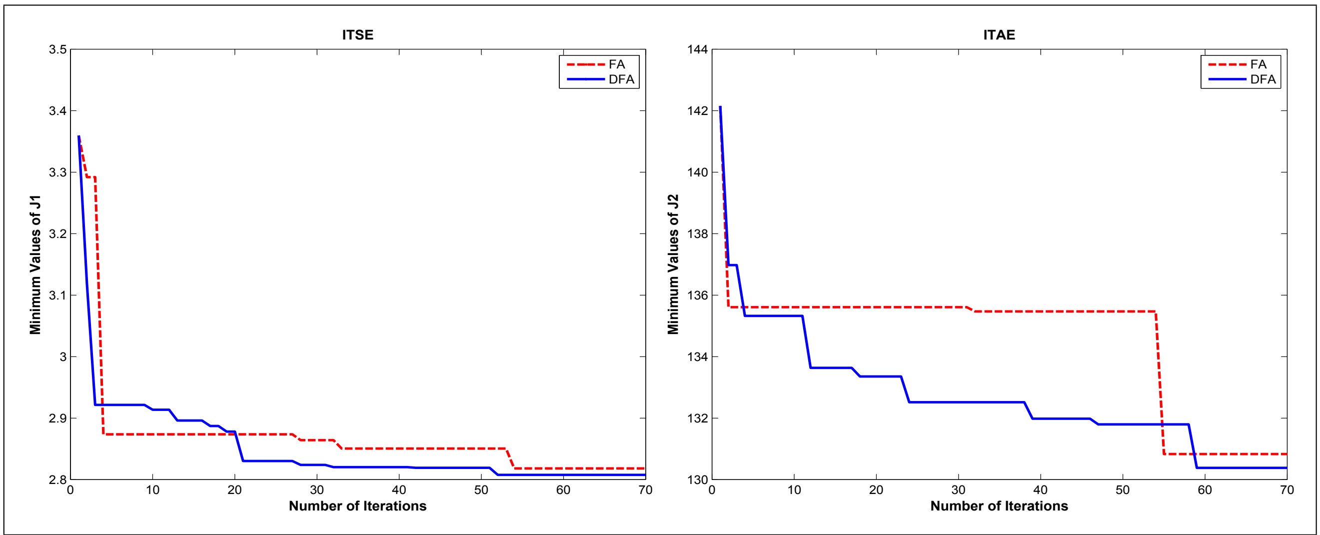

Fig. 6. Convergence rates of the ITAE and ITSE functions for DFA and FA algorithms.

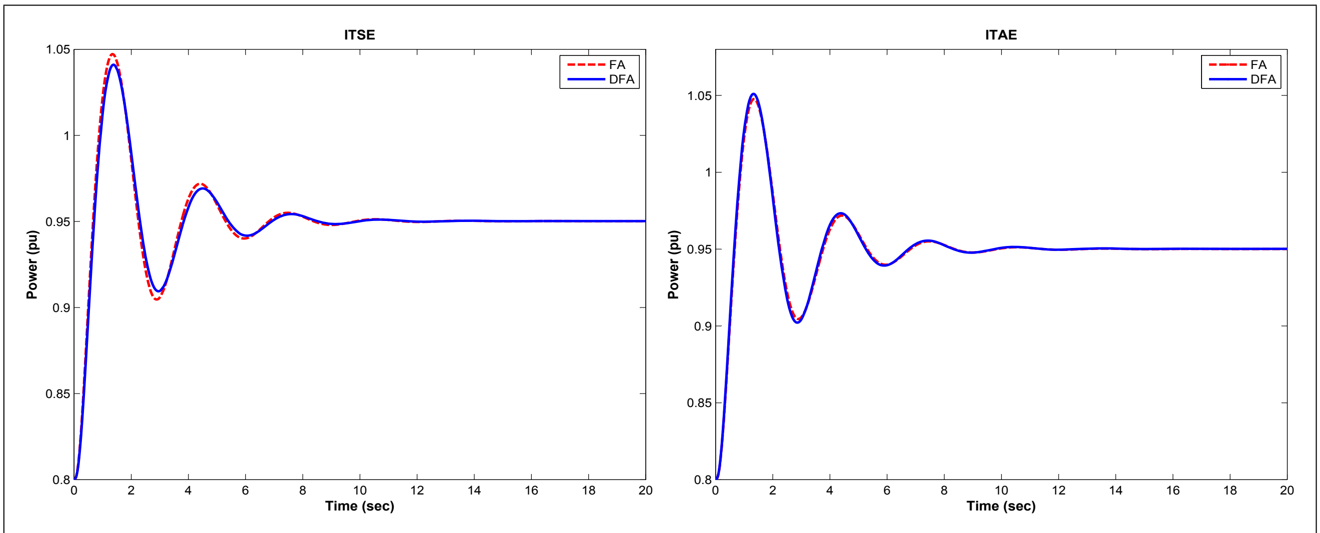

Fig. 7. Power responses of the gas turbine fuzzy-FOPID controllers based on the ITAE and ITSE functions.

time frame. The variations of the best parameters γ, β_0, α during the algorithm iterations are presented in Fig. 9 for the ITAE and ITSE functions, respectively. According to this figures, it is obvious that there is no a best predefined combination for the entire evolution procedure. Figure 10 shows the responses of the gas turbine power plant for an 3% frequency drop, both for the ITSE and ITAE functions, respectively. Note that the fuzzy-FOPID approach is able

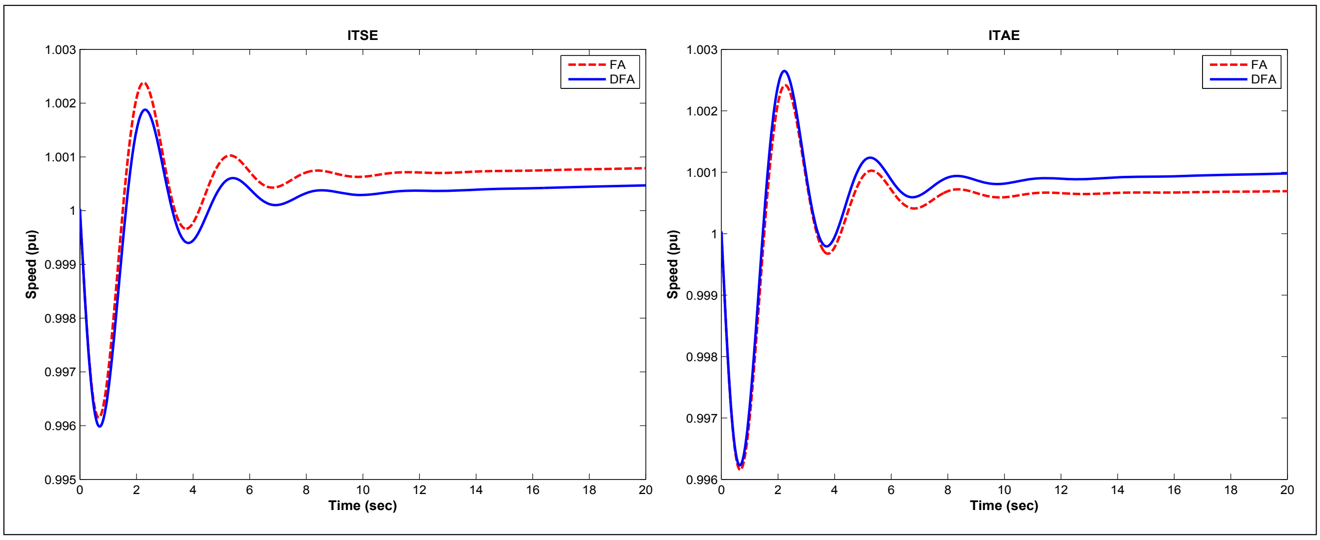

Fig. 8. Speed responses of the gas turbine fuzzy-FOPID controllers based on the ITAE and ITSE functions.

Table 4. Obtained objective function for J_1 and J_2 in 10 runs.

Algorithms	Best	Worst	Average
FA(J_1)	2.81827	2.88191	2.85569
DFA(J_2)	2.8077	2.87034	2.8283
FA(J_1)	130.8322	134.2166	131.6446
DFA(J_2)	130.3823	131.2111	130.8739

to quickly recover from the sudden frequency drop and bring back the frequency to its desired level.

6. CONCLUSION

This paper proposed a Fractional Order Fuzzy-PID approach for the control of the speed loop of a heavy-duty gas turbine. The gains of the fuzzy-FOPID controller are optimally tuned using an enhanced firefly algorithm. This latter implements a dynamic procedure to choose the most appropriate combinations of the population size, the absorption coefficient, the attractiveness coefficient, and the step size scaling factor to quickly auto-tune and optimize the controller gains. Analytical and simulation results confirmed the superiority of the dynamic approach and its ability to enhance the convergence rate and final optimization value of the FA.

REFERENCES

Forbes, A. (2018). High-efficiency gas turbines will play a growing role in the energy transition. https://www.ge.com/power/transform/article.transform .articles.2018.sep.high-efficiency-gas-turbines

GlobalData (2018). Gas turbines for thermal power, Update 2018 - Global Market Size, Competitive Landscape, Key Country Analysis, and Forecast to 2022.

Haji Haji, V., Fekih, A., Monje, C.A., and Fakhri Asfestani, R. (2019). H_2, H_∞, H_2/H_∞ and $\mu-synthesis$ controllers for the speed and temperature control of a real gas turbine unit in a combined cycle power plant. *Energy Sci Eng.*, 118. https :// doi.org/10.1002/ese3.425.

Haji Haji, V., and Monje, C.A. (2017). Fractional order fuzzy-PID control of a combined cycle power plant using particle swarm optimization algorithm with an improved dynamic parameters selection. *Appl. Soft. Comput.*, 58, 256–264.

Haji Haji, V., and Monje, C.A. (2018). Fractional-order PID control of a chopper-fed DC motor drive using a novel firefly algorithm with dynamic control mechanism. *Soft. Comput.*, 22, 6135–6146.

Jurado, F., Ortega, M., Cano, A., and Carpio, J. (2002). Neuro-fuzzy controller for gas turbine in biomass-based electric power plant. *Electr. Pow. Syst. Res.*, 60, 123–135.

Kakimoto, N., amd Baba, K. (2003). Performance of gas turbine-based plants during frequency drops. *IEEE Trans. Power. Syst.*, 18, 1110–1115.

MKT (2018). Advantages and disadvantages of gas and steam turbines power plants. https://thermogenpower.com/advantages-and-disadvantages-of-gas-and-steam-turbines-power-plants/

Mansouri Mansourabad, A., Hamidi Beheshti, M.T., and Simab, M. (2013). A hybrid PSO-fuzzy-PID controller for gas turbine speed control. *International Journal of Control and Automation*, 6, 13–24.

Efe, M.O. (2011). Neural network assisted computationally simple $PI^\lambda D^\mu$ control of a quadrotor UAV. *IEEE Trans. Ind. Electron.*, 7, 354–361.

Podlubny, I. (1999). Fractional Differential Equations, Academic Press, San Diego, CA.

Rowen, W.I. (1983). Simplified mathematical representations of heavy-duty gas turbines. *ASME J. Eng. Power.*, 105, 865–869.

Senthilnath, J., Omkar, S., and Mani, V. (2011). Clustering using firefly algorithm: performance study. *Swarm Evol. Comput.*, 1, 164–171.

Yang, X.S., Hosseini, S.S.S., and Gandomi, A.H. (2011). Firefly algorithm for solving non-convex economic dispatch problems with valve loading effect. *Appl. Soft. Comput.*, 12, 1180–1186.

Zhang, Q. (2000). Dynamic modeling of a combined cycle plant for power system stability studies, *IEEE Power Engineering Society Winter Meeting, Conference Proceedings*, Singapore, vol. 2, pp. 1538–1543.

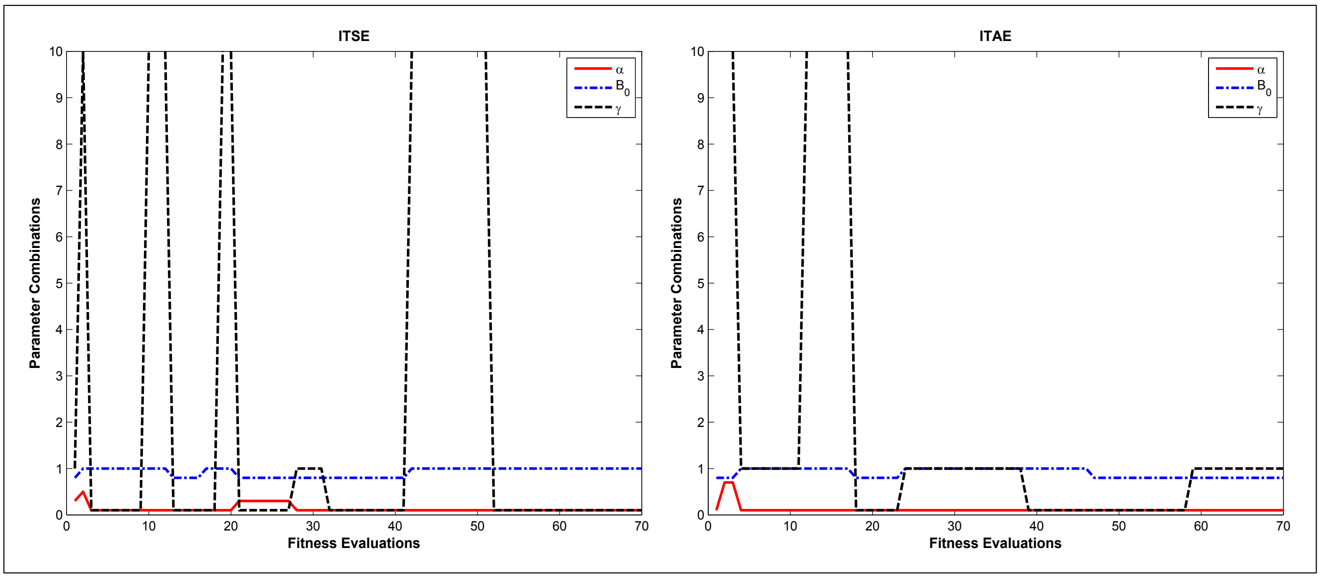

Fig. 9. Best obtained parameters for the ITAE and ITSE functions during the evolution procedure.

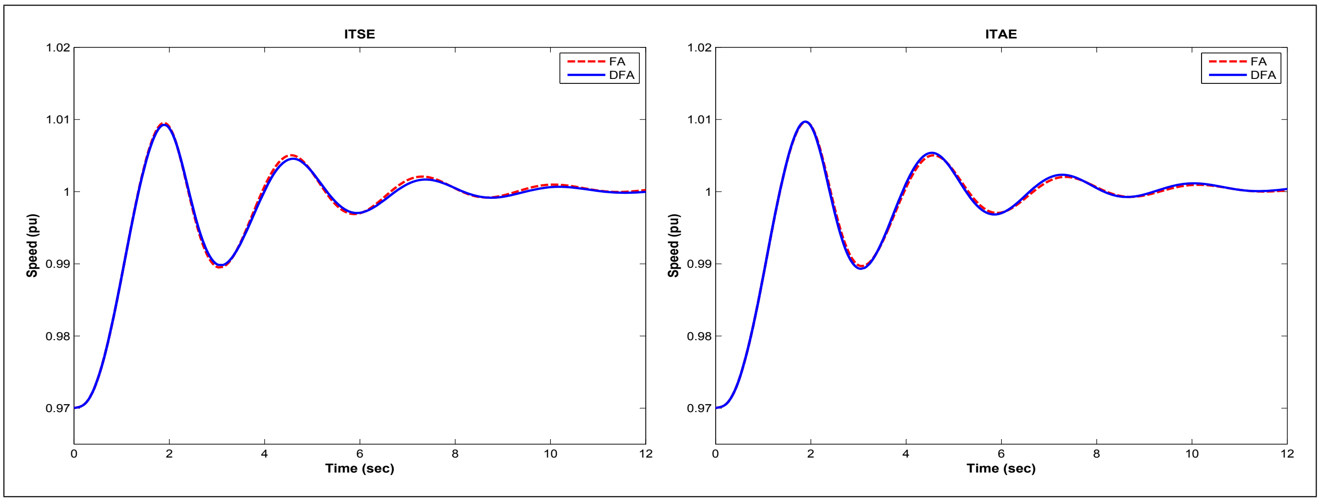

Fig. 10. Output speed for a 3% frequency drop.

Appendix A. GAS TURBINE MODEL PARAMETERS

Table A.1. Gas Turbine Model Parameters.

Parameter	Value
Fuel demand lower limit (Min)	-0.1
Fuel demand upper limit (Max)	1.5
Fuel system coefficient (b)	0.05
Fuel system coefficient (c)	1
Fuel system coefficient (a)	1
Fuel system time constant (T_F)	0.4
Fuel system feedback (K_F)	0
Turbine and exhaust delay (E_{TD})	0.04
Compressor discharge volume time constant (T_{CD})	0.2
Combustion reaction time delay (E_{CR})	0.01
Temperature controller integration rate (T_T)	450 (^oC)
Turbine rated exhaust temperature (T_R)	950 (^oC)
Turbine rotor time constant (T_I)	15.64