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Research Article

Optimization of PID Controller for Brushless DC Motor by using Bio-inspired Algorithms

[1]Sanjay Kr. Singh, [2]Nitish Katal and [3]S.G. Modani
[1]Anand International College of Engineering, Jaipur, Rajasthan, India
[2]Department of Electronics and Communication Engineering, Amity University, Rajasthan, India
[3]Malaviya National Institute of Technology, Jaipur, Rajasthan, India

Abstract: This study presents the use and comparison of various bio-inspired algorithms for optimizing the response of a PID controller for a Brushless DC Motor in contrast to the conventional methods of tuning. For the optimization of the PID controllers Genetic Algorithm, Multi-objective Genetic Algorithm and Simulated Annealing have been used. PID controller tuning with soft-computing algorithms comprises of obtaining the best possible outcome for the three PID parameters for improving the steady state characteristics and performance indices like overshoot percentage, rise time and settling time. For the calculation and simulation of the results the Brushless DC Motor model, Maxon EC 45 flat ɸ 45 mm with Hall Sensors Motor has been used. The results obtained the optimization using Genetic Algorithms, Multi-objective Genetic Algorithm and Simulated Annealing is compared with the ones derived from the Ziegler-Nichols method and the MATLAB SISO Tool. And it is observed that comparatively better results are obtained by optimization using Simulated Annealing offering better steady state response.

Keywords: Brushless DC motor, controller tuning, genetic algorithm, PID controllers, PID optimization, simulated annealing, ziegler nichols

INTRODUCTION

The generic dc motors have high efficiency and have a high starting torque versus falling speed characteristics, which helps to counter the sudden rise in load and thus find their application in industries since ages (Katal *et al*., 2012). Since dc motors suffer from the deficiencies like:

- The lack of periodic maintenance
- Mechanical wear-outs
- Acoustic noise
- Sparkling
- Brushes effect, etc., so, the current focus has adapted the development of brushless direct current models

The Brushless Direct Current (BLDC) motors are typically dc voltage driven permanent synchronous motors and are gaining grounds in aeronautics, medicine, consumer and industrial automation applications. The BLDC motors have better:

- Speed versus torque characteristics
- High efficiency
- High dynamic response
- Noiseless operation
- Low maintenance and many more (Padmaraja, 2003; Krause *et al*., 2002) and the best advantage in terms of higher ratio of torque obtained to the size of motor

Proportional, Integral and Derivative-PID controllers are playing an imperative role in the industrial control applications. Because of their simplicity and wide acceptability, they are still the best solutions for the industrial control processes (Åström *et al*., 2001). Modern industrial controls are often required to regulate the closed-loop response of a system and PID controllers account for the 90% of the total controllers used in the industrial automation. The simple block level representation of the PID controller based system can be obtained as in Fig. 1.

The general equation for a PID controller for the above figure can be given as Norman (2003):

$$C(s) = Kp.e(s) + Ki\int e(s)dt + Kd\,\frac{de(s)}{dt}$$

where,
K_p, K_i and K_d = The controller gains
$C(s)$ = Output signal

Corresponding Author: Sanjay Kr. Singh, Anand International College of Engineering, Jaipur, Rajasthan, India

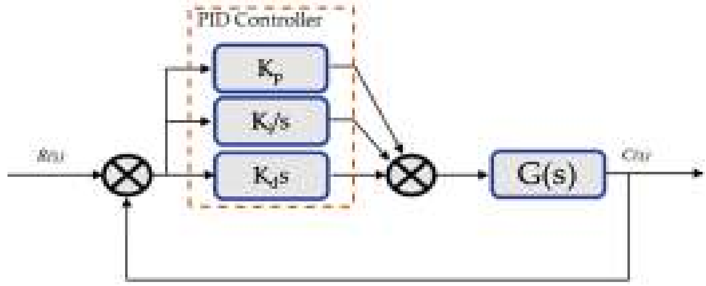

Fig. 1: Block diagram of a PID control based system with unity feedback

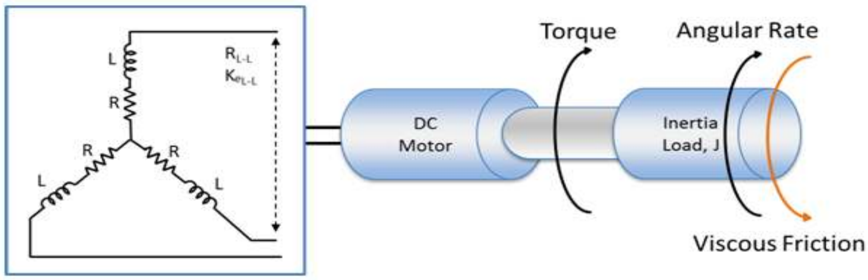

Fig. 2: Schematic diagram of a BLDC Motor

$e(s)$ = The difference between the desired output and output obtained

In this study, the optimization of the PID controller gains has been carried out using Genetic Algorithms (GA), Multi-Objective Genetic Algorithm (MOGA) and Simulated Annealing (SA) in contrast to the Ziegler-Nichols (ZN) method and the automated tuning provided in MATLAB viz. SISO Tool. Then, these gain parameters can be optimally tuned with respect to the objective function, stated as "Sum of the integral of the squared error and the squared controller output deviated from its steady-state" (Goodwin *et al*., 2001).

According to the results obtained in this paper, considerably better results have been obtained in the case of the Simulated Annealing (SA) when compared to those obtained by Genetic Algorithm, Multi-objective Genetic Algorithm, Ziegler-Nichols method and the MATLAB SISO Tool in respective the step response of the system.

MATERIALS AND METHODS

Mathematical model of brushless DC motor: In this study the model of a BLDC motor has been considered, unlike the dc motor, the commutation of the BLDC can only be done by electronic control (Padmaraja, 2003). The operation of BLDC motor can be realized in many modes (phases), generally 3 phases. The main advantage of 3-Phase is better efficiency and quiet low torque and has best precision in control (Texas Instruments).

In this study, the use of Maxon EC flat ϕ 45 mm, brushless, 30 Watt motor with Hall Sensors has been used. The schematic illustration of the considered system is shown in Fig. 2.

Using Kirchhoff's Voltage Law (KVL), the following equation is obtained:

$$V_s = R_i + L.\frac{di}{dt} + e \tag{1}$$

where,

V_s = The DC Source voltage
i = Armature current

Similarly while considering the mechanical properties, Newton's second law of motion gives the relative dependence of torque of the system as the product of the inertial load, J and the rate of angular velocity, ω_m, as:

$$J\frac{d\varpi_m}{dt} = \sum T_i \tag{2}$$

$$T_e = k_f \varpi_m + J\frac{d\varpi_m}{dt} + T_L \tag{3}$$

where,

T_e = Electric torque
k_f = Friction constant
J = Rotor inertia
ω_n = The angular velocity
T_L = The supposed mechanical load

Table 1: Parameters and units of maxon motor

Maxon motor data	Unit	Value
Value at nominal voltage		
Nominal voltage	V	12.000
No load speed	Rpm	4370
No load current	mA	151
Nominal speed	Rm	2860
Nominal torque (max. continuous torque)	mNm	58.000
Nominal current (max. continuous current)	A	2.140
Stall torque	mNm	255
Starting current	A	10.000
Maximum frequency	%	77.000
Characteristics		
Terminal resistance phase to phase	Ω	1.200
Terminal inductance phase to phase	mH	0.560
Toque constant	mNm/A	25.500
Speed constant	rpm/V	37.400
Speed/torque gradient	rpm/mNm	17.600
Mechanical time constant	Ms	17.100
Rotor inertia	gcm^2	92.500
Number of phases	-	3.000

Table 2: Parameters of the PID controller calculated by ziegler-nichols method

Ziegler nichols PID parameters	Value
K_p	0.3160
K_i	31.3000
K_d	0.0008

Table 3: Parameters of the PID controller calculated by SISO based automated designing

SISO tuned parameters	Value
K_p	0.265000
K_i	17.867000
K_d	-0.000586

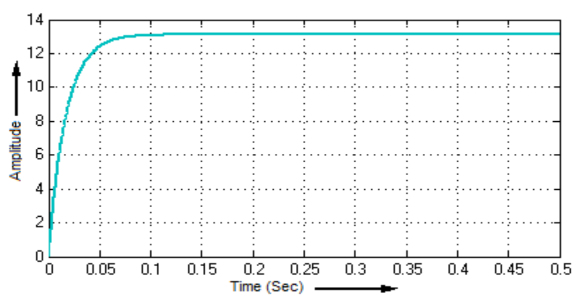

Fig. 3: Open loop step response of the system

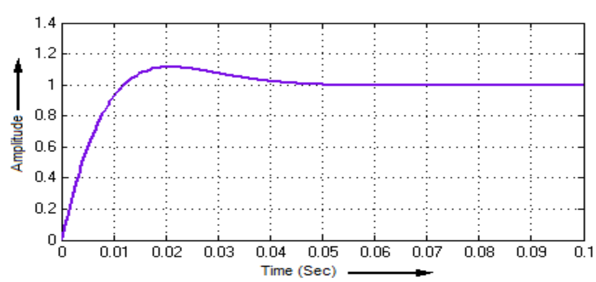

Fig. 4: Closed loop step response of the system with ZN-PID controllers

The electrical torque and the back emf can be obtained as:

$$e = k_e \varpi_m \quad \text{and} \quad T_e = k_t \varpi_m \tag{4}$$

where,
k_e = The back emf
k_t = Torque constant

Thus the transfer function can be obtained by using the ratio of the angular velocity, ω_m to source voltage V_s, as:

$$G(s) = \frac{\varpi_m}{V_s} = \frac{\frac{1}{k_e}}{\tau_m.\tau_e.s^2 + \tau_m.s + 1} \tag{5}$$

Since the system is symmetrical and a three phase, thus constants used above in Eq. (5) can be given as:

The Mechanical, τ_m (Time Constant) and Electrical, τ_e (Time Constant):

$$\tau_m = \frac{R.3J}{k_e k_t} \quad \text{and} \quad \tau_e = \frac{L}{3.R}$$

The mathematical model of the Maxon BLDC motor (Sabudin, 2012) can be modelled on the parameters listed in Table 1.

Thus by using the above listed parameters, the value for K_e, τ_m and τ_n can be obtained as:

$\tau_e = 155.56 * 10 - 6\ Kgm^2$; $\tau_m = 0.0171$ and $K_e = 0.763$ *v-sec/rad*

Therefore, the transfer function $G(s)$ becomes:

$$G(s) = \frac{13.11}{2.66 \times 10^{-6} \cdot s^2 + 0.0171 \cdot s + 1} \tag{6}$$

Equation (6) gives us the open-loop transfer function for the Brushless DC Maxon Motor.

Design of the PID controllers:

Tuning of PID gains using ziegler nichols: One of the most widely used method for the tuning of the PID controller gains is to use the open loop response as inferred by Ziegler-Nichols (ZN), yet this method finds its in application till the ratio of 4:1 for the first two peaks in the closed loop response (Goodwin *et al.*, 2001), which leads to a oscillatory response of the system.

Initially, the unit step function (Fig. 3 and 4) is derived and hence as suggested by the Ziegler-Nichols, the parameters required can easily be estimated as given in Table 2.

MATLAB SISO automated designing: The SISO tool accelerates the PID controller design by its GUI based interactive compensator tuning. The tuning can be done interactively by balancing the poles and zeros on Bode or root-locus plots, or can be optimized by meeting the pre-defined time and frequency domain requirements by the system. The SISO tuned PID controllers for the BLDC Motor can be seen in the Fig. 5 (Table 3).

Table 4: Parameters used in optimization by genetic algorithm

Genetic algorithm optimized parameters	Value
K_p	5.0001
K_i	0.0039
K_d	5e-4

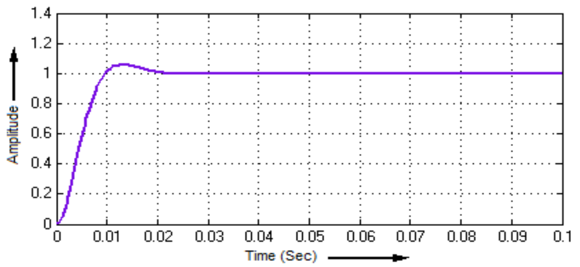

Fig. 5: Closed loop step response of the system with SISO-PID controllers

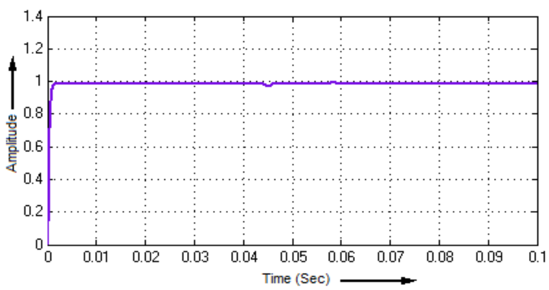

Fig. 6: Closed loop step response of the system with GA-PID controllers

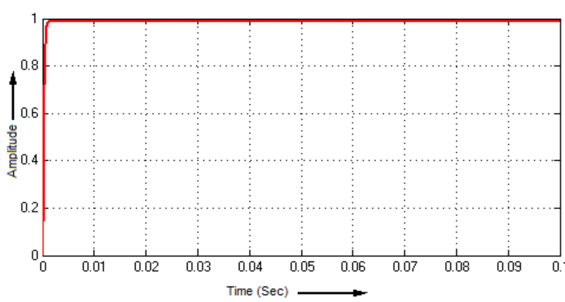

Fig. 7: Closed loop step response of the system with Mobj-GA-PID controllers

PID controller optimization using genetic algorithm: Since the designing of the PID controllers by Ziegler-Nichols methods, gives an oscillatory response; hence the controller parameters obtained from ZN are not optimum for the directly implementation for the plant, so their organized optimization must be carried out, so that the better possible parameters can be estimated and implemented for the best performance of the system.

So, the Genetic Algorithms can be used along with the parameters obtained by the Ziegler-Nichols response, as the parameter determined by ZN helps in the determination of the lower and upper bound limits to be used for the estimation of parameters using Genetic Algorithms.

The steps involved in the implementation of the Genetic Algorithms for a control system are as follows:

- Generating the initial, random population of the fixed numbered individuals for the declaration of the initial ranges for *Kp*, *Ki* and *Kd*
- For the evaluation of the fitness integral it minimizes the integral square error, followed by the selection of the fittest individuals of the population
- Reproduction among members of population
- Crossover of the reproduced chromosome followed by the mutation operations and the selection of the best individuals i.e., Survival of the Fittest
- Looping the step 2 till the pre-defined convergence is obtained

The optimization of the system has been designed and simulated in MATLAB and Genetic Algorithm toolbox, with population size of 100, scattered crossover and migration direction in both sides. Table 4 shows the GA optimized PID parameters and Fig. 6 shows the GA-PID step response of the system.

PID controller optimization using multi-objective genetic algorithm: Optimization of PID's using multi-objective genetic algorithm aims at using the controlled elitist genetic algorithm which boosts obtaining the better fitness value of the individuals and if the fitness value is less, it still favors increasing the diversity of the population (Deb, 2001). Diversity is controlled by the elite members of the population; elitism is controlled by Pareto fraction and at Pareto Front also bound the number of individuals. Optimization of the PID controllers using Multi-Objective Genetic Algorithm aims at improving the objective function of the both the objectives used by obtaining an optimal Pareto solution. In this study, two objective functions have been used F1 (ITSE) and F2 (OS %):

$$ITSE = O_1 = \int_0^{\infty} t \cdot |e(t)|^2 \, dt \quad and$$

$$Overshoot \quad \%age = 100 \times e^{\left(\frac{-\varsigma\pi}{\sqrt{1-\varsigma^2}}\right)}$$

where,
ς = The Damping ratio

First objective function ITSE i.e., Integral Time Square Error tries to minimize the larger amplitudes by supressing the persistent larger errors (Jean-Pierre, 2004) while second objective function overshoot percentage; thus forcing the solution towards the global best solution.

The system implementation and optimization has been carried out in MATLAB and SIMULINK

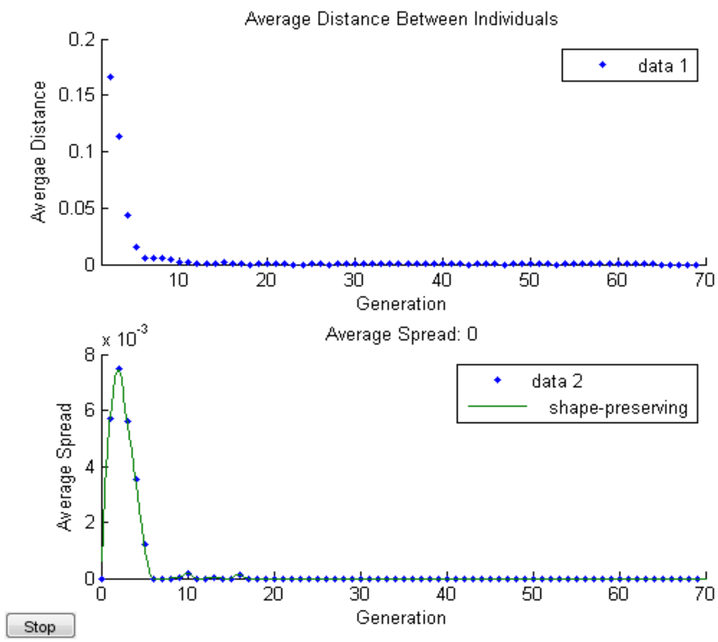

Fig. 8: (a) Average distance between individuals of the generated populations and, (b) average pareto spread between individuals of the generated populations

Table 5: Parameters used in optimization by multi-objective genetic algorithm

Multi-objective genetic algorithm optimized parameters	Value
K_p	5.2938
K_i	0.0042
K_d	4.5024e-4

Table 6: Parameters used in optimization by simulated annealing

Simulated annealing optimized parameters	Value
K_p	5.0424
K_i	0.0040
K_d	3.0454e-4

environment using Global Optimization Toolbox. The population size of 45 has been considered, with adaptive feasible mutation function, heuristic crossover and the selection of individuals on the basis of tournament with a tournament size of 2. A hybrid function of Fitness Goal Attain (*fgoalattain*) is used which further minimizes the function after GA terminates. After the optimization the PID parameters are shown in Table 5 along with the controller response in Fig. 7 and 8.

PID controller optimization using simulated annealing: Simulated annealing is a global optimization algorithm, as the name suggests, the muse comes from metallurgic annealing, which involves relation between the relation between the statical mechanics and multivariate optimization (Berrsimas, 1993). It follows the technique involving heating the material followed by controlled cooling, fetching increased crystal size and reduced deformities.

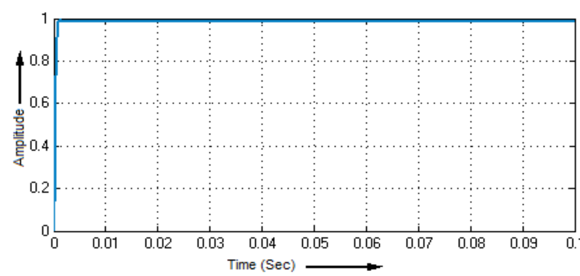

Fig. 9: Closed loop step response of the system with GA-PID controllers

In Simulated Annealing (SA), at each iteration, a new point is randomly generated and its distance from the current point is the function of probability distribution with a scale proportional to temperature. The randomly generated points are accepted if they lower the objective but in order to help the algorithm to search for global solution and to omit the trapping of the algorithm in local minima, some points are so chosen that they raise the objective. With the advent of algorithm, the temperature is decreased leading in reduction of the extent of search to converge the minima.

The optimization has been carried out in MATLAB and SIMULINK environment with the help of Global Optimization Toolbox using Simulated Annealing function. For simulated annealing, the Boltzmann Annealing function has been used with an exponentially updating temperature. The parameters obtained after optimization are in Table 6 and the response of the PID controller with SA optimised parameters is shown in

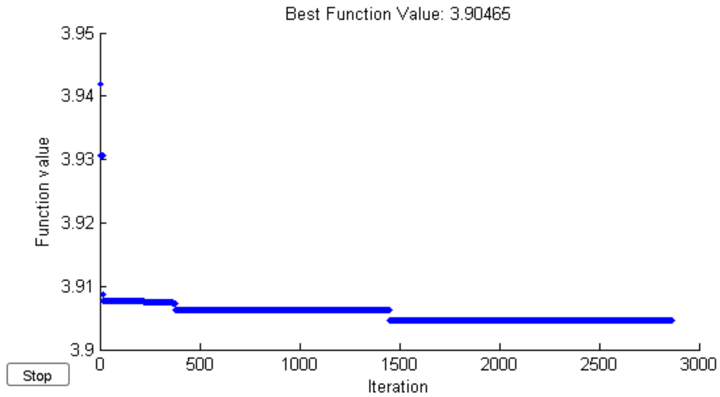

Fig. 10: Plot for the best function value of the simulated annealing optimization

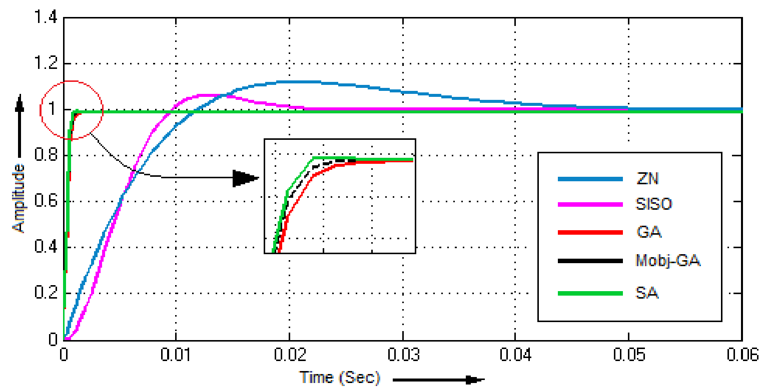

Fig. 11: Compared closed loop step response of the ZN, SISO and GA-PID controllers

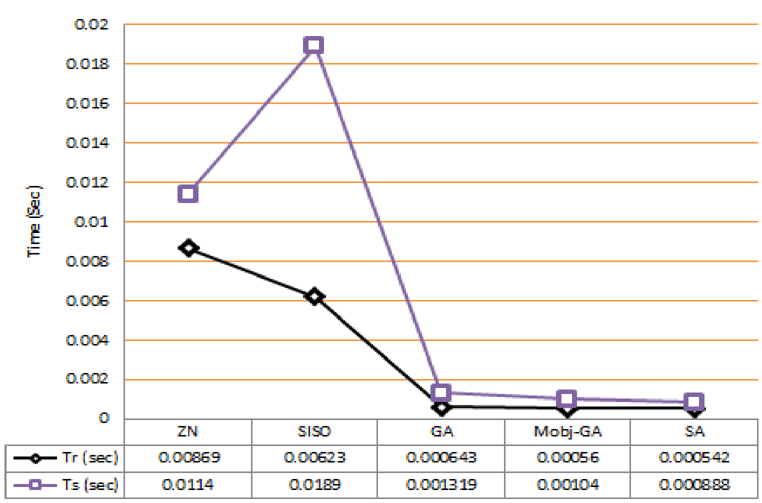

Fig. 12: Compared variation in rise and settling times of the ZN, SISO and GA-PID controllers

Table 7: Comparison of the results

Methods of design	Overshoot (%)	Tr (sec)	Ts (sec)
Ziegler-nichols method	11.50	0.008690	0.011400
MATLAB SISO tool	5.88	0.006230	0.018900
Genetic algorithm	0.00	0.000643	0.001319
Multi-objective genetic algorithm	0.00	0.000560	0.001040
Simulated annealing	0.00	0.000542	0.000888

Fig. 9. Figure 10 shows the Plot for the Best function value of the Simulated Annealing optimization.

RESULTS AND DISCUSSION

In this study, a dynamic model of a Maxon BLDC Motor has been designed and implemented in

MATLAB along with the optimization using the various bio-inspired algorithms like Genetic Algorithm, Multi-objective Genetic Algorithm and Simulated Annealing. The value of parameters obtained using Ziegler-Nichols rules (Ziegler and Nichols, 1942) were used in the formation of the boundary limits for the intervals for the design parameters in soft-computing algorithms, to control the controller by minimizing the error and hence the determination of the optimum parameters for the plant.

The computation of the PID parameters is done by the Ziegler-Nichols rules, SISO Design Tool, Genetic Algorithms, Multi-objective Genetic Algorithm and Simulated Annealing and their closed loop step responses are shown in Fig. 4 to 9. Figure 11 shows the comparative response of all the controllers over a single plot and Fig. 12 shows the comparative values of the various steady-state parameters. Table 7 shows the numeric comparison of the results of various steady-state parameters. From Table 7 and Fig. 11 and 12, it's clearly evident that Simulated Annealing solutions present zero oscillatory response and reduced rise and settling times in contrast to the Ziegler-Nichols, SISO, Genetic Algorithm and Multi-objective Genetic Algorithm. Concluding, Simulated Annealing offers superior results in terms of system performance and controller output for the tuning of PID controllers.

CONCLUSION

The use of Simulated Annealing for optimizing the PID controller parameters as presented in this study offers advantages of decreased overshoot percentage, rise and settling times for the Maxon EC flat ϕ45 mm, brushless, 30 Watt motor. Results when compared with the other tuning mythologies as presented in this study, the Simulated Annealing has proved superior in achieving the steady-state response and performance indices.

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