PSO Tuned PID Controller for DC Motor Speed Control

Aaditya Sharma, Veena Sharma, and O. P. Rahi

Abstract The purpose of this paper is to plan a PSO algorithm application to tune the parameters of the PID regulator. This paper employs the model of a DC motor as a plant. As the conventional tuning of PID regulator using Ziegler–Nichols (Z-N) technique delivers a major overshoot, the present-day heuristics approach named particle swarm optimization (PSO) has been utilized here to upgrade the proficiency of old conventional technique. Four different performance indices (IAE, ISE, ITAE, and ITSE) are used while comparing PSO-based PID and ZN-PID in this paper. The results have shown the better performance of the PID tuning utilizing the PSO-based optimization approach.

Keywords IAE · ISE · ITAE · ITSE · PID · PSO · Z-N

List of Symbols

b	Motor Viscous Friction Constant
$C(s)$	Controller Transfer Function
e	Control Error Signal
e_V	Back EMF
$G(s)$	Plant Transfer Function
i	Armature Current
IAE	Integral Absolute Error
ISE	Integral Square Error

A. Sharma (✉) · V. Sharma · O. P. Rahi
Department of Electrical Engineering, National Institute of Technology Hamirpur, Hamirpur, HP 177005, India

V. Sharma
e-mail: veena@nith.ac.in

O. P. Rahi
e-mail: oprahi@nith.ac.in

S. Suhag et al. (eds.), *Control and Measurement Applications for Smart Grid*, Lecture Notes in Electrical Engineering 822,
https://doi.org/10.1007/978-981-16-7664-2_7

ITAE	Integral Time Absolute Error
ITSE	Integral Time Square Error
J	Moment of Inertia of Rotor
K	Motor Torque Constant
Kt	EMF Constant
Kw	EMF Constant
K_p	Proportional Gain
K_i	Integral Gain
K_d	Derivative Gain
L	Inductance
OF	Objective Function
PID	Proportional Integral Derivative
PSO	Particle Swarm Optimization
PV	Process Variable
r	Input Signal
R	Armature Resistance
T	Torque
y	Output Signal
Z-N	Ziegler–Nichols

1 Introduction

Though the control theory has touched new heights, even today the most inescapable form of feedback compensation comes from the PID controller. PID controllers have become the backbone of the motion control system in the industry [1]. Self-adjusting PID has transformed the shape of the industrial world and made it suitable for engineers to bring the finest control of a plant. The output generated by the PID controller is the aggregation of the outputs of proportional, integral, and derivative controllers. As per the literature concerned, above 95% of industrial control is done by the PID controllers. A PID regulator ceaselessly figures an error $e(t)$ as the distinction amid the process variable (PV) and set point (SP). PID's accuracy and optimized automatic control make it a problem solver. As it has all the necessary dynamics like reduced rise time, steady-state error and improves the transient response which makes the system stable. Ziegler–Nichols developed the first tuning rules with two methods [2]. The first one is for an open-loop system, and the second one is for the closed-loop system. The Z-N adjusting in feedback loop requires the critical gain and critical period. In this technique, the controller is put on automatic mode while the integral and derivative actions are shut off. The regulator gain is raised until an interruption which causes continuous oscillations in the process variable. As the computational approaches are modernized in recent times for the sake of desirable results in industrial process control via tuning of the regulator's optimization, algorithms came into role [3–8]. The principal proponents of the PSO algorithm were Kennedy and Eberhart in 1995 [9]. In order to get the finest results, different agents are employed. These agents move in a group and every agent tries to provide the finest outcome. In PSO individual particle's latest location is decided by a velocity term which redirects the attraction of global best and its own best throughout the history of the particle and random coefficients.

2 Problem Formulation

The block diagram of a feedback control system of the closed-loop type is shown in Fig. 1. PID regulator comprises of following gains (a) proportional, (b) integral, and (c) derivative. The scheme of feedback type is reflected in Fig. 1 where reference input, control error, and measured output are denoted as r, e, y correspondingly.

In this control scheme shown in Fig. 1, the target system (plant) is represented as $G(s)$ and regulator as $C(s)$, which is specified by Eq. (1) as given below:

$$C(s) = K_{\mathrm{p}} + K_{\mathrm{i}}/s + K_{\mathrm{d}}s \tag{1}$$

where K_{p}, K_{i}, K_{d} are separately recognized as proportional, integral, and derivative coefficients of the PID regulator that are heading for adjustment.

DC Motor Modeling

See Fig. 2.

System equations are represented as follows:

Torque equation:

$$T = K * i \tag{2}$$

Back EMF equation:

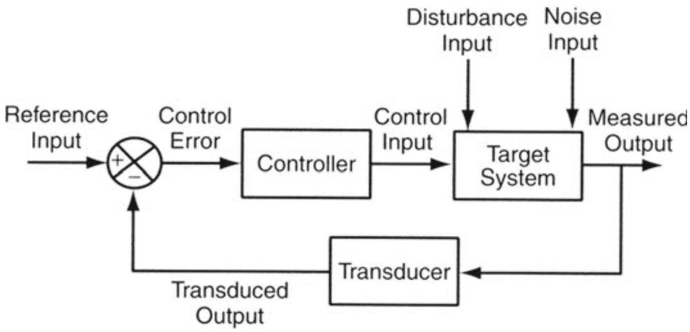

Fig. 1 Block diagram representation of a feedback control system [10]

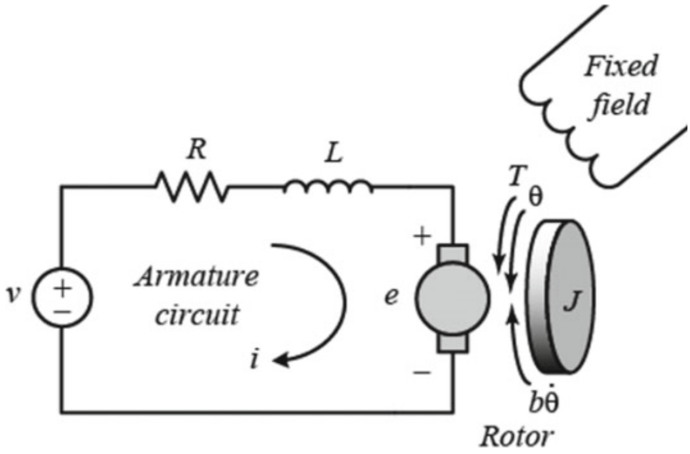

Fig. 2 Electrical equivalent circuit of DC motor [11]

$$e_V = K_W * (\theta') \tag{3}$$

Torque equation using Newton's second law:

$$T = J * (\theta'') + b * (\theta') \tag{4}$$

Terminal voltage equation using Kirchhoff's voltage law:

$$V = L\frac{di}{dt} + R * I + K_W * (\theta') \tag{5}$$

Using Eqs. (2)–(5) in Laplace domain, we get

$$P(s) = \frac{(\theta'(s))}{V(s)} = \frac{K}{(Js + b)(Ls + R) + K * Kw} \tag{6}$$

Using the block diagram, the obtained transfer function between angular position and voltage is given in Fig. 3:

$$G(s) = \frac{\theta(s)}{V(s)} = \frac{K}{JLs^3 + (BL + JR)s^2 + (BR + K * Kw)s + K * Kt} \tag{7}$$

The physical parameters of the DC motor are given below:

$J = 1$ kg m^2, $B = 8$ N m s, $R = 1\ \Omega$, $L = 1$ H, $K = 1$ N m/A, $K_W = 15$ V/Rad/s and Kt = 15 V/Rad.

On substituting the above parameters in Eq. (7), the transfer function model of the DC motor is given by Eq. (8):

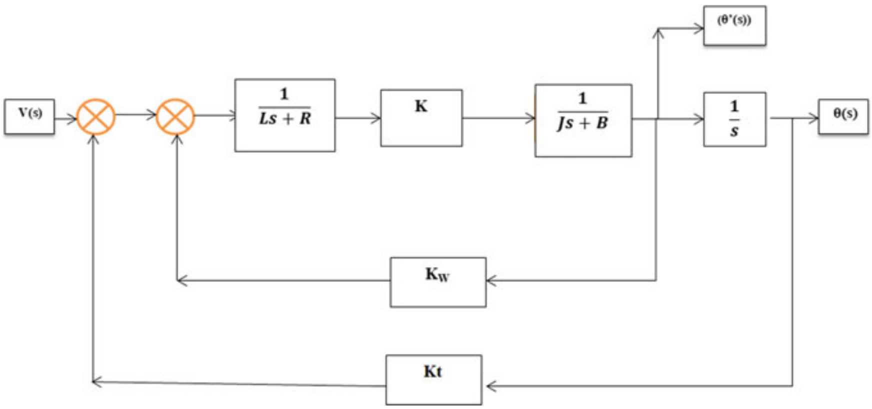

Fig. 3 Block diagram of DC motor [12]

$$G(s) = 1/\left(s^3 + 9s^2 + 23s + 15\right) \tag{8}$$

Moreover, error-based performance index to design an optimum PID regulator is being used in this work. Error-based performance criteria are utilized as a measurable tool to rate the functioning of the PID regulator system which has been designed in this paper. Utilizing the instant strategy an 'ideal framework' can be frequently planned, and a bunch of coefficients of PID regulator in the framework can be changed accordingly to achieve the necessary conditions. Framework execution of PID regulator is portrayed in ISE, IAE, ITAE, and ITSE. They are characterized as follows:

$$\text{ISE} = \int_0^\infty e^2(t)\mathrm{d}t \tag{9}$$

$$\text{IAE} = \int_0^\infty |e(t)|\mathrm{d}t \tag{10}$$

$$\text{ITAE} = \int_0^\infty t|e(t)|\mathrm{d}t \tag{11}$$

$$\text{ITSE} = \int_0^\infty te^2(t)\mathrm{d}t \tag{12}$$

3 Solution Methodology

A. Two solution methodologies have been used in this research work. First one is tuning of PID using conventional Ziegler–Nichols (ZN) technique, and the second one is PID tuning using particle swarm optimization.
B. Z-N METHOD USED FOR TUNING OF PID REGULATOR

We have used the second technique of ZN METHOD, i.e., tuning of PID with closed-loop method. This approach demands that the critical gain and critical time to be calculated. The derivative time constant (T_d) is kept at zero while integral time constant (T_i) is retained at infinity. All this can be accomplished by altering the regulator gain (K_u) until continuous oscillations are met by the system (Table 1).

C. PSO-BASED PID REGULATOR TUNING

The transformative computational procedure is the base of PSO optimization. Collective ventures in a school of fish and group of birds were the reason and inspiration which brought out a new technique of optimization, and the proponents of this technique were Kennedy and Eberhart in 1995. A very few numbers of parameters are assigned to the PSO algorithm in contrast to other metaheuristic algorithms. Initialization of a cluster of simulated birds is done with random locations *Xi* and velocities *Vi*. Every bird in the swarm is scattered arbitrarily in the first stage throughout the *D* dimensional search space. Every particle within the cluster starts adjusting its velocity and location under the inspection of the objective function, companion's experiences and their own experiences. Every particle remembers its best position attained by it along with the best global place attained by any other particle in the swarm throughout the exploration of an optimal solution. $X_I = (x_{i1}, x_{i2}, \ldots, x_{iD})$ is the representation of the *i*th particle. Gbest denoted by symbol g is a representative of the finest particle amid all particles in the population. $P_I = (p_{i1}, p_{i2}, \ldots, p_{iD})$ is represented as pbest and $V_I = (v_{i1}, v_{i2}, \ldots, v_{iD})$ is represented as velocity of the particle.

The particles are modified corresponding to the equations below:

$$V_{id}{}^{n+1} = w * V_{id}{}^{n} + c_1 * \text{rand}() * \left(p_{id}{}^{n} - X_{id}{}^{n}\right) + c_2 * \text{rand}() * \left(p_{gd}{}^{n} - X_{id}{}^{n}\right) \quad (13)$$

$$X_{id}{}^{n+1} = X_{id}{}^{n} + V_{id}{}^{n+1} \quad (14)$$

In this, two positive acceleration coefficients c_1 and c_2 are used. A random number between 0 and 1 is produced by rand () operator, and n represents iteration. The new

Table 1 Parameters used for Ziegler–Nichols closed-loop tuning [13]

Controller type	KP	Ti	Td
P	0.5 Kcr	∞	0
PI	0.45 Kcr	1/1.2 Pcr	0
PID	0.6 Kcr	0.5 Pcr	0.125 Pcr

results of the speed and location in comparison with the earlier results from its own top experience are evaluated by Eq. (7). According to Eq. (14), the particle moves toward a novel location. Shi and Eberhart [14] proposed the concept of inertial weight which was missing in the primary algorithm suggested by Kennedy and Eberhart. The work reports that the global exploration is facilitated by large inertia weight factor while local exploration is facilitated by a small weight factor. Moreover, particle swarm optimization exploration potential can be enhanced for multi-dimensional issues by regulating the weight of inertia which was proposed by various scientists. Later in 1999 Clerc [15] presented his own version of PSO which resulted in guaranteed convergence of algorithm for inertial weight $w = 0.729$.

D. EXECUTION OF PSO TUNED PID CONTROLLER

The PSO-based technique has been used using MATLAB/Simulink model as shown in Figs. 4 and 5.

Metaheuristic optimization can be implemented to alter PID regulator gains to guarantee the performance of the regulator at minimal functioning states. In Eq. (8), using the plant transfer functions K_p, $K_{i,}$ and K_d are altered using PSO in offline mode. It primarily creates an initial horde of particles in a domain characterized by a matrix. Every particle denotes a unique result for PID coefficients. The values of these coefficients are varied on a scale between 0 and 100. As there are primarily three coefficients, we have to solve for three-dimensional space with velocity and position characterized by matrices of dimension 3× swarm size. For PSO algorithm, these values such as swarm size of 40, acceleration coefficients $c_1 = c_2 = 1.494$, and weight of inertia (w) which is reducing linearly from 0.9 to 0.4 as the number of iterations reach its maximum value are referred from the existing literature [17].

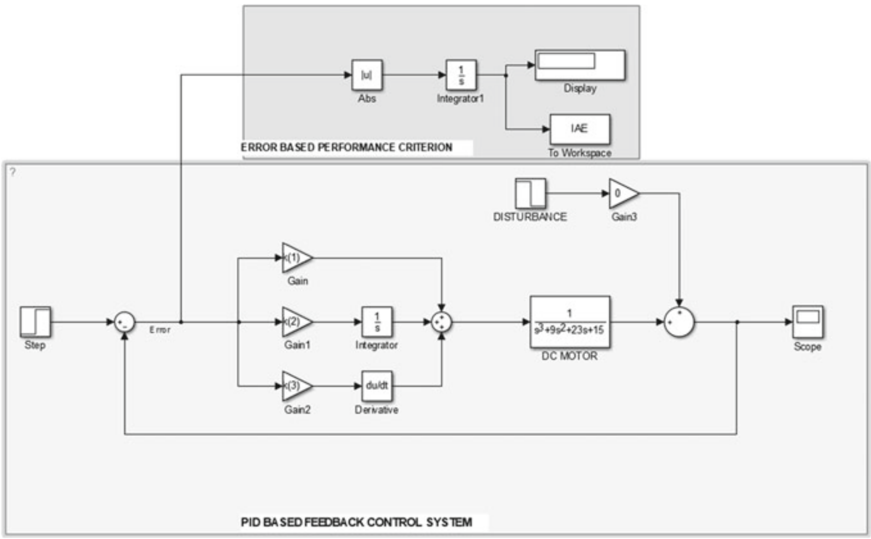

Fig. 4 Simulink diagram of the PID-based control system [16]

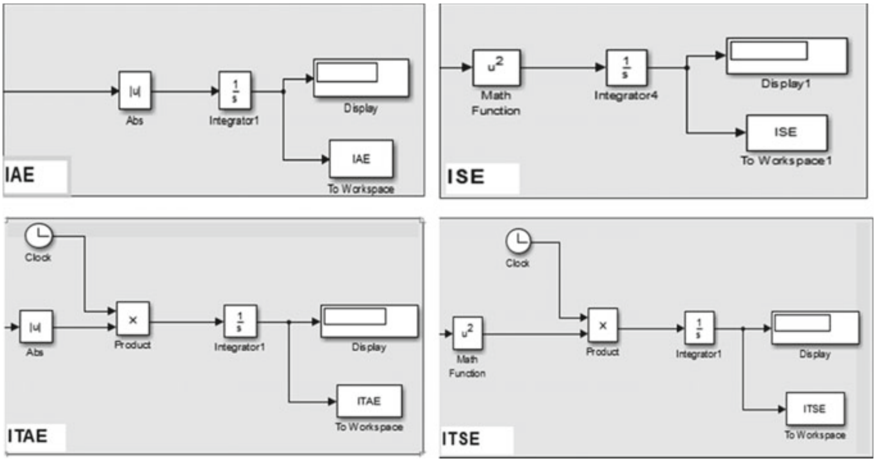

Fig. 5 Simulink diagram of four performance indices

4 Results and Discussion

Using the traditional Ziegler–Nichols (Z-N) technique, the step response of the system creates large overshoot, instead superior performance is found with the execution of the PSO tuned PID controller. As compared to the Z-N technique, PSO has less overshoot and less settling time. The PSO process is simulated for 50 iterations. Collective step response is plotted for the Z-N method and PSO tuned controller with different performance index shown in Fig. 6. In Fig. 7 on applying step disturbance signal on the transducer side, PSO tuned PID controller attenuates the disturbance successfully and Z-N tuned PID controller takes more time to settle down.

Figure 8 denotes the plot between the fitness function value and the number of iterations. This plot shows how the value of performance index converges to minimum value with the increase in the number of iterations.

Relative outcomes for the PID regulators are shown beneath in Table 2 where the performance of step response is measured centered on the peak value, overshoot, settling time, rise time, and peak time.

Table 2 shows the relative effect in which step response parameters for different tuning techniques are evaluated, and PSO shows a significant enhancement in the values of overshoot values and settling time.

Table 3 exhibits the controller gains optimized for respective methods. For different performance indices used in the PSO algorithm, PID regulators show different optimized gains.

Table 3 exhibits the performance index used in the PSO algorithm and ZN method. It shows those different optimized gains that lead to different step response parameters.

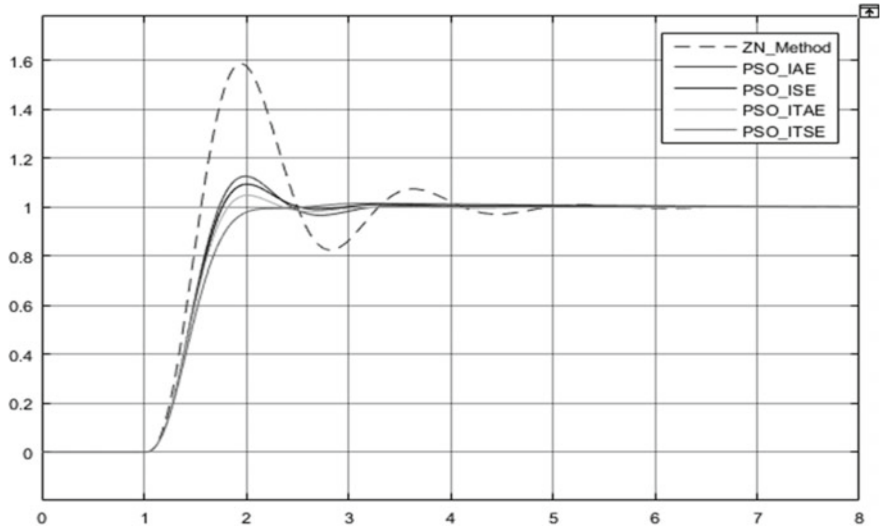

Fig. 6 Step response plot for Z-N and PSO tuned PID controller

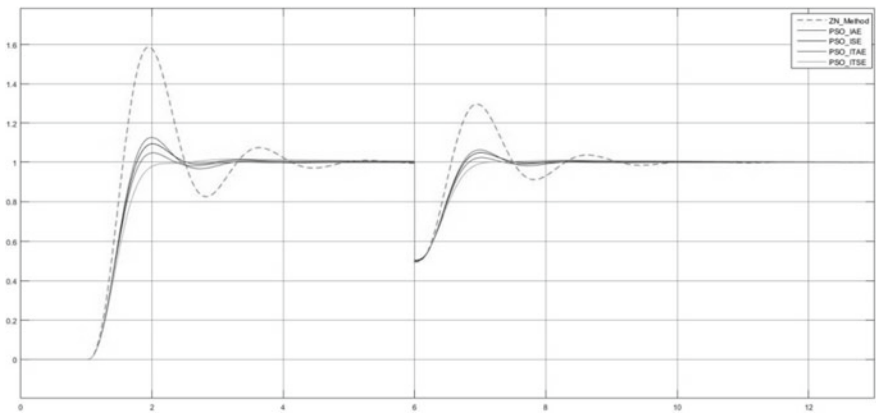

Fig. 7 Step response plot for Z-N and PSO tuned PID controller when a disturbance is introduced at the transducer side

5 Conclusion and Future Scope

As inferred from the results that PSO works well as compared to that of traditional Ziegler–Nichols method by attenuating the disturbance produced at the transducer side. PSO in comparison with Ziegler–Nichols method has less overshoot and less settling time, and because of this, it becomes a more efficient computational method. While a few parameters are to be adjusted in PSO, it has an edge over Ziegler–Nichols

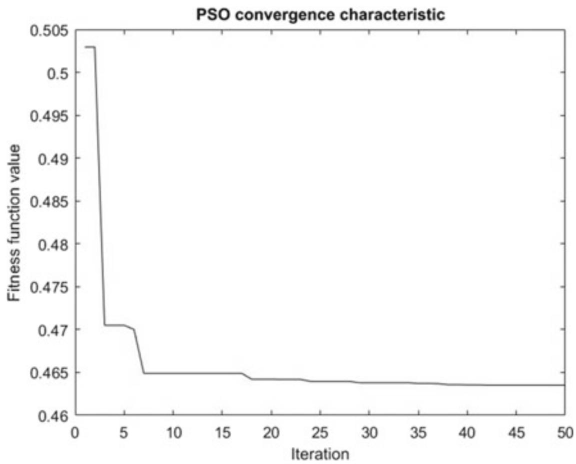

Fig. 8 Performance index plot of PSO algorithm of IAE type

Table 2 Parameters of step response for proportional integral derivative controllers

Technique used for tuning	Peak	Overshoot	Peak time	Rise time	Settling time
ZN METHOD	1.5876	58.8061	1.9496	0.3319	4.6684
PSO_IAE	1.1267	12.6882	1.9949	0.4506	2.9590
PSO_ISE	1.0943	9.2795	2.0083	0.4696	2.3884
PSO_ITAE	1.0486	4.8792	2.0151	0.4949	2.2451
PSO_ITSE	1.0165	1.3478	3.2557	0.5905	2.0216

Table 3 Controller gains optimized for respective methods

Technique used for tuning	K_p	K_i	K_d
ZN METHOD	115.2	175.9	18.9
PSO_IAE	100.0	38.1933	19.8595
PSO_ISE	100.0	40.2469	22.6765
PSO_ITAE	100.0	34.0138	24.5222
PSO_ITSE	93.4686	34.5348	28.7630

method and successfully gives optimal solutions. Moreover, indistinguishable performances are observed when PSO tuned PID regulators are optimized with various error-based performance indices. In relation to future scope other metaheuristic optimization techniques such as moth flame optimization (MFO) can be carried out for tuning of PID regulator as it has achieved a faster rate of convergence and less peak overshoot value. Here in this paper, third-order DC motor is used as a plant; however, higher-order DC motor model can also be considered for further research.

References

1. Tavakoli S, Sadeghi J, Griffin I, Fleming PJ (2016) PI controller tuning for load disturbance rejection using constrained optimization. Int J Dyn Control 6(1):188–199
2. Ogata K (1987) Modern control systems. Prentice Hall, Minneapolis, MN
3. Gaing Z-L (2004) A particle swarm optimization approach for optimum design of PID controller in AVR system. IEEE Trans Energy Convers 19(2):384–391
4. Zhao J, Li T, Qian J (2005) Application of particle swarm optimization algorithm on robust PID controller tuning. In: Advances in natural computation. Springer, Berlin/Heidelberg, pp 948–957
5. Mahony TO, Downing CJ, Fatla K (2000) Genetic algorithm for PID parameter optimization: minimizing error criteria. In: Process control and instrumentation. University of Stracthclyde, pp 148–153
6. Wang Q, Spronck P, Tracht R (2003) An overview of genetic algorithms applied to control engineering problems. In: Proceedings of the international conference on machine learning and cybernetics (IEEE Cat. No.03EX693)
7. Latha K, Rajinikanth V, Surekha PM (2013) PSO-based PID controller design for a class of stable and unstable systems. ISRN Artif Intell 2013:1–11
8. Vincent A, Nersisson R (2017) Particle swarm optimization based PID controller tuning for level control of two tank system. IOP Conf Ser Mater Sci Eng 263:052001
9. Kennedy J, Eberhart RC (1995) Particle swarm optimization. In: Proceedings of IEEE international conference on neural networks (Perth, Australia). IEEE Service Center, Piscataway, NJ, pp IV: 1942–1948
10. Hellerstein J (2004) Introduction and overview, Ch 1. In: Feedback control of computing systems. Wiley, New York City, NY, pp 3–28
11. Messner B, Tilbury D (2017) DC motor speed: system modeling. Accessed 01 Feb 2021. [Online]. Available: https://ctms.engin.umich.edu/CTMS/index.php?example=MotorSpeed§ion=SystemModeling
12. Zaccarian L (2012) Lecture notes, topic: "Dc motors: dynamic model and control techniques". University of Rome, Rome
13. Ziegler JG, Nichols NB (1993) Optimum settings for automatic controllers. ASME J Dyn Syst Meas Control 115(2B):220–222
14. Shi Y, Eberhart R (1998) A modified particle swarm optimizer. In: Proceedings of the IEEE world congress on computational intelligence, pp 69–73
15. Clerc M (1999) The swarm and the queen: towards a deterministic and adaptive particle swarm optimization. In: Proceedings of the conference on evolutionary computation, pp 1951–1957
16. Bequette BW (2003) Process control: modeling, design, and simulation. Prentice Hall PTR, India
17. Solihin MI, Tack LF, Kean ML (2011) Tuning of PID controller using particle swarm optimization (PSO). Int J Adv Sci Eng Inf Technol 1(4):458