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Optimal PID control of a brushless DC motor using PSO and BF techniques

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Abstract This paper presents a Particle Swarm Optimization (PSO) technique and bacterial foraging (BF) technique for determining the optimal parameters of (PID) controller for speed control of a brushless DC motor (BLDC) where the (BLDC) motor is modeled in simulink in Matlab. The proposed technique was more efficient in improving the step response characteristics as well as reducing the steady-state error, rise time, settling time and maximum overshoot.

1. Introduction

There are mainly two types of DC motor used in the industry. The first one is the conventional DC motor where the flux is produced by the current through the field coil of the stationary pole structure. The second type is the brushless DC motor (BLDC motor) where the permanent magnet provides the necessary air gap flux instead of the wire-wound field poles [1].

There are many modern control methodologies such as nonlinear control, optimal control, variable structure control and adaptive control have been widely proposed for speed control of a brushless permanent magnet DC motor [2]. However, these approaches are either complex in theoretical basics or difficult to implement [3]. PID controller with its three terms functionality covering treatment for transient and steady-state response offers the simplest and gets most efficient solution to many real world control problems [4]. In spite of the simple structure, optimally tuning gains of PID controllers are quite difficult. Recently, the computational intelligence has proposed bacterial foraging (BF) technique and Particle Swarm Optimization (PSO) technique for the same purpose.

2. Brushless DC motor

Permanent magnet DC motors use mechanical commutators and brushes to achieve the commutation. The stator of BLDC motor is the coil, and the rotor is the permanent magnet. The stator develops the magnetic field to rotate the rotor. Hall effect sensor detects the rotor position as the commutating signals. Therefore, BLDC motors use permanent magnets

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instead of coil in the armature and so do not need brushes. In this paper a three-phase and two-pole BLDC motor is studied. The speed of the BLDC motor is controlled by means of a three-phase and half-bridge pulse width modulation (PWM) inverter. Fig. 1 shows torque/speed characteristics with reference speed is 100 rpm, and this kind of motor not only has the advantages of DC motor such as better velocity capability and no mechanical commutator but also has the advantages of AC motor such as simple structure, higher reliability and free maintenance. In addition, brushless DC motor has the following advantages: smaller volume, high torque, and simple system structure. So it is widely applied in areas which needs high performance drive [5].

Fig. 2 shows line to line voltage v_{ab} with respect to time, the characteristics equations of a BLDC motor are described by Eqs. (1)–(4) [2] and Fig. 3 shows the three-phase currents of the stator.

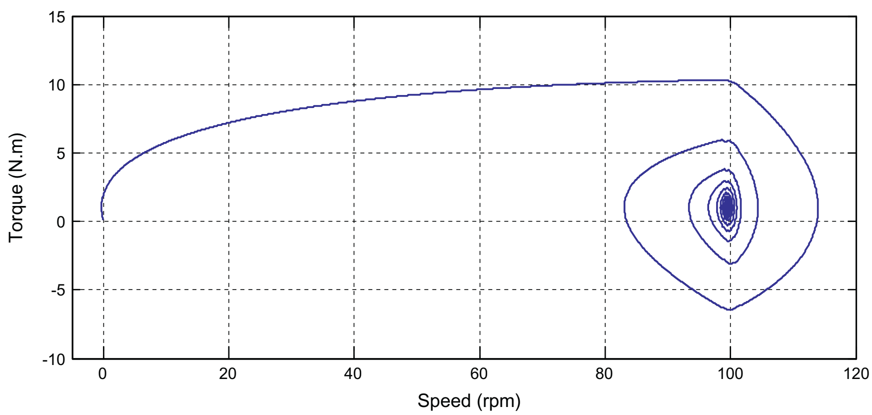

Figure 1 Torque/speed characteristics.

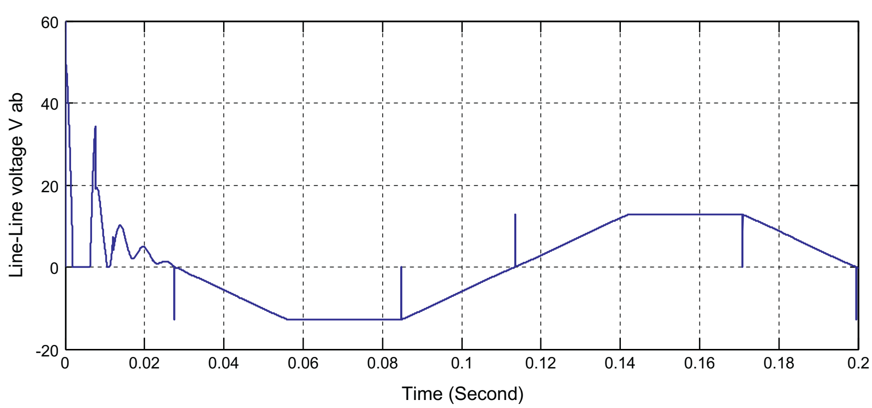

Figure 2 Line-line voltage v_{ab}.

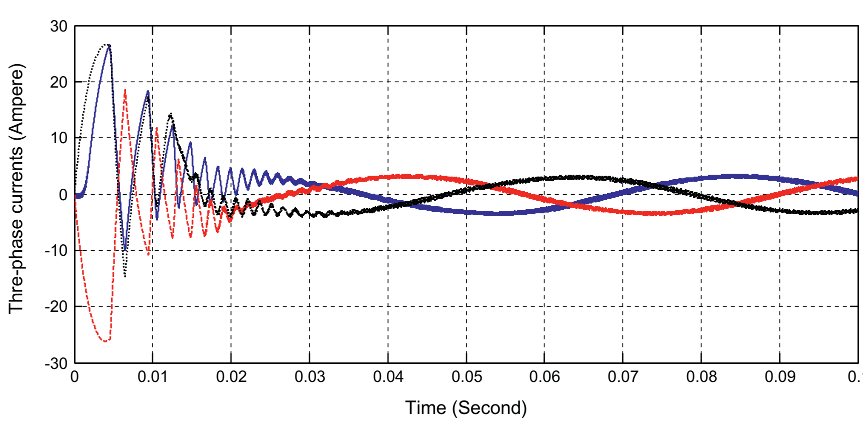

Figure 3 Three-phase currents of the stator.

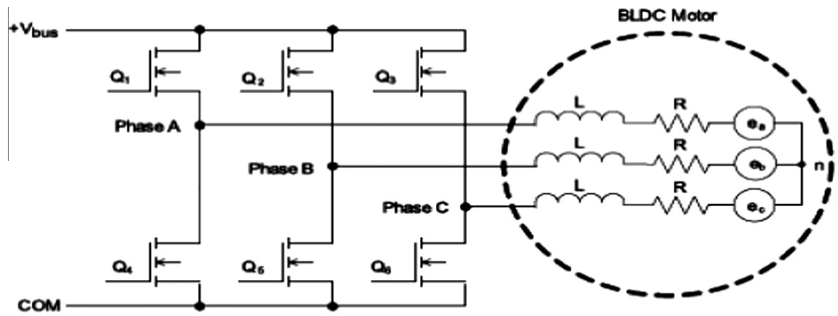

Figure 4 Three-phase full-bridge power circuit for BLDC motor drive.

$$v_{app}(t) = L\frac{di(t)}{dt} + R \cdot i(t) + v_{emf} \tag{1}$$

$$v_{emf} = k_b \cdot \omega(t) \tag{2}$$

$$T(t) = k_t \cdot i(t) \tag{3}$$

$$T(t) = J\frac{d\omega(t)}{dt} + D \cdot \omega(t) \tag{4}$$

where $v_{app}(t)$ is the applied voltage, $\omega(t)$ is the motor speed, L is the inductance of the stator, $i(t)$ is the current of the circuit, R is resistance of the stator, v_{emf} is the back electromotive force, T is the torque of motor, D is the viscous coefficient, J is the moment of inertia, k_t is the motor torque constant, k_b is the back electromotive force constant, and Fig. 4 shows the equivalent circuit of three-phase full-bridge power circuit for (BLDC) motor drive.

The motor used in simulation process has the next parameter values as follows:

– Volt: 24 V (DC)
– Power: 52 W
– Nominal speed: 200 rpm
– Nominal current: 4.2 A
– No. of poles (p) = 4
– R (phase stator resistance): 0.6 Ω
– λ_m (the amplitude of flux linkage): 0.105 Wb.Turn
– L (self-inductance of each coil)
– M (mutual inductance between any two coils)
– ($L - M$): 0.0015
– D (viscous coefficient): zero
– T (Max. torque): 8 N m

3. PID controller

PID controller has been used widely for processes and motion control system in industry. The transfer function of PID controller is shown in Fig. 5. The control system performs poorly in characteristics and even it becomes unstable, if improper values of the controller tuning constants and used. So it becomes necessary to tune the controller parameters to achieve good control performance with the proper choice of tuning constants [6].

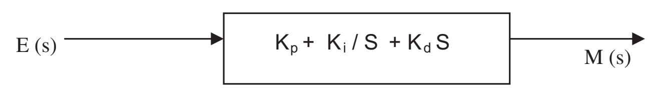

Figure 5 Transfer function of PID controller.

where:

E(s) is error input signal, M(s) is manipulated output signal. K_p is proportional gain, K_i is integral gain and K_d is derivative gain.

These parameters K_p, K_i and K_d are chosen to meet prescribed performance criteria, classically specified in terms of rise and settling times, overshoot, and steady-state error. In this paper PSO and BF techniques used to find the optimal values of parameters K_p, K_i and K_d of (PID) controller for BLDC motor speed control system. Fig. 6 shows the block diagram of optimal PID control for the BLDC motor.

4. Particle Swarm Optimization (PSO)

To search the optimal PID controller, the PSO algorithm is applied. Here the potential solutions called particles, where it is metaphor of fish in fish schools or bird in bird flocks. These particles are randomly initialized and fly through multidimensional space. During the flying, these particles update its velocity and position based on the experience of its own and the whole population [7,8].

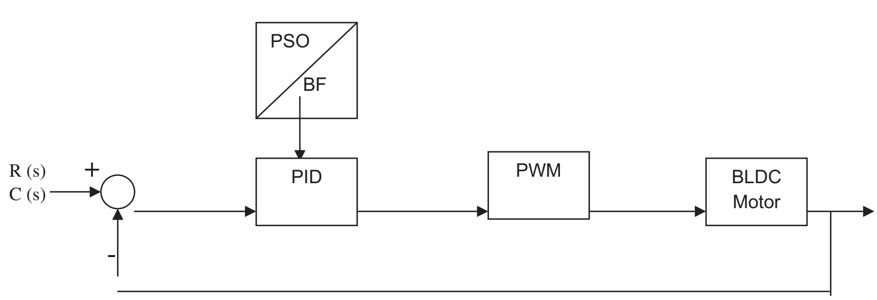

Figure 6 The optimal PID control.

The updating procedure will drive the particle swarm to move toward region with better fitness function and every particle is gathered around the point with the best fitness functions. In the proposed PSO method each particle contains three members k_p, k_i and k_d. It means that the search space has three dimensions and particles must fly in a three dimensional space.

According to the background of PSO and simulation of swarm of bird, Kennedy and Eberhart developed a PSO concept. Namely, PSO is basically developed through simulation of bird flocking in three-dimensional space. The positive of each agent is represented by xyz axes position and also the velocity is expressed by v_x (the velocity of x-axis, v_y (the velocity of y-axis) and v_z (the velocity of z-axis). Modification of the agent position is realized by the position and velocity information.

Bird flocking optimizes certain fitness function. Each agent has known its best value so far (pbest) and its xyz position. This information is analogy of personal experiences of each agent. Moreover, each agent knows the best value so far in the group (gbest) among pbests. This information is analogy of knowledge of how the other agents around them have performed. Namely, each agent tries to modify its position using the following information:

– the current positions (x, y, z)
– the current velocities (v_x, v_y, v_z)
– the distance between the current positions and pbest
– the distance between the current position and gbest.

This modification can be represented by the concept of velocity. Velocity of each agent can be modified by the following equations [9]:

$$v_i^{k+1} = w \times v_i^k + C_1 rand_1 \times (pbest_i - s_i^k) + C_2 rand_2 \times (gbest - s_i^k) \tag{5}$$

where:

- *pbest*: particle best position of agent i
- *gbest*: global particle best position of the group
- v_i^k: velocity of agent i at iteration k, w: weighting function
- C_j: correction factor, *rand*: random number between 0 and 1
- *rand*: random number between 0 and 1
- s_i^k: current position of agent i at iteration k.

The following weighting function is usually utilized in (6):

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \tag{6}$$

where:

- $w_{\max}$: final weight, $w_{\min}$: initial weight
- $iter_{\max}$: maximum iteration number, *iter*: current iteration number.

Using the above equation, a certain velocity, which gradually gets close to pbest and gbest can be calculated. The current position (searching point in the solution space) can be modified by the following equation:

$$S_i^{k+1} = S_i^k + V_i^{k+1} \tag{7}$$

5. Bacterial Foraging Optimization

To tackle complex search problems of the real world, scientists have been drawing inspiration from nature and natural creatures for years. Optimization is at the heart of many natural processes like Darwinian evolution, group behavior of social insects, and the foraging strategy of other microbial creatures. Natural selection tends to eliminate species with poor foraging strategies and favor the propagation of genes of species with successful foraging behavior since they are more likely to enjoy reproductive success.

Since a foraging organism or animal takes necessary action to maximize the energy intake per unit time spent for foraging, considering all the constraints presented by its own physiology such as sensing and cognitive capabilities, environment (e.g., density of prey, risks from predators, physical characteristics of the search space), the natural foraging strategy can lead to optimization and essentially this idea can be applied to solve real world optimization problems. Based on this concept, Passino proposed an optimization technique known as the Bacterial Foraging Optimization Algorithm (BFOA) [10].

Recently, search and optimal foraging of bacteria have been used for solving optimization problems. To perform social foraging, an animal needs communication capabilities and over a period of time it gains advantages that can exploit the sensing capabilities of the group. This helps the group to predate on a larger prey, or alternatively, individuals could obtain better protection from predators while in a group [11].

The common type of bacteria is *Escherichia coli* (*E. coli*) [11]. Its behavior and movement come from a set of six rigid spinning (100–200 r.p.s) flagella, each driven as a biological motor. An *E. coli* bacterium alternates through running and tumbling, the chemotactic actions of the bacteria are modeled as follows:

– In a neutral medium, if the bacterium alternatively tumbles and runs, its action could be similar to search.
– If swimming up a nutrient gradient (or out of noxious substances) or if the bacterium swims longer (climb up nutrient gradient or down noxious gradient), its behavior seeks increasingly favorable environments.
– If swimming down a nutrient gradient (or up noxious substance gradient), then search action is like avoiding unfavorable environments.

Therefore, it follows that the bacterium can climb up nutrient hills and at the same time avoids noxious substances. The sensors it needs for optimal resolution are receptor proteins which are very sensitive and possess high gain. That is, a small change in the concentration of nutrients can cause a significant change in behavior. This is probably the best-understood sensory and decision-making system in biology [11].Mutations in *E. coli* affect the reproductive efficiency at different temperatures, and occur at a rate of about 10^{-7} per gene per generation. *E. coli* occasionally engages in a conjugation that affects the characteristics of the population. There are many types of taxis that are used in bacteria such as, aerotaxis (attracted to oxygen), phototaxis (light), thermotaxis (temperature), magnetotaxis (magnetic lines of flux) and some bacteria can change their shape and number of flagella (based on the medium) to reconfigure in order to ensure efficient foraging in a variety of media. Bacteria could form intricate stable spatio-temporal patterns in certain semisolid nutrient substances and they can survive through a medium if placed together initially at its center. Moreover, under certain conditions, they will secrete cell-to-cell attractant signals so that they will group and protect each other, the bacterial foraging system consists of four principal mechanisms, namely chemotaxis, swarming, reproduction, and elimination dispersal [10]. Below each of these processes will be described by.

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + c(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \tag{8}$$

where $\theta^i(j, k, l)$ represents ith bacterium at jth chemotactic, kth reproductive and lth elimination-dispersal step. $c(i)$ is the size of the step taken in the random direction specified by the tumble (run length unit), where Δ indicates a vector in the random direction whose elements lie in $[-1, 1]$, Δ^T is the transpose of Δ.

The cell-to-cell signaling in *E. coli* swarm may be represented by the following function:

Table 1 PSO-PID controller.

PSO (PID) controller	K_p	K_i	K_d	Peak time (t_p)	Rise time (t_r)	Settling time (t_s)	Max. over shoot M_p %	Steady-state error e_{ss}
With	6.6397	1	0.0028	0.0051	0.0030	0.0047	0.5698	0.0368
Without	1	0	0	0.0055	0.0030	0.0163	13.956	0.5248

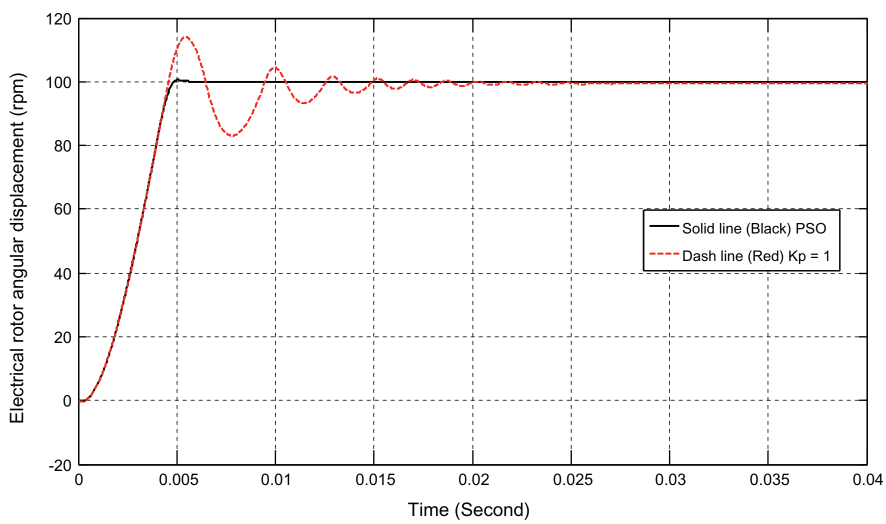

Figure 7 Step response of the closed loop system with PSO-PID controller using ITSE based fitness function and without PSO-PID controller.

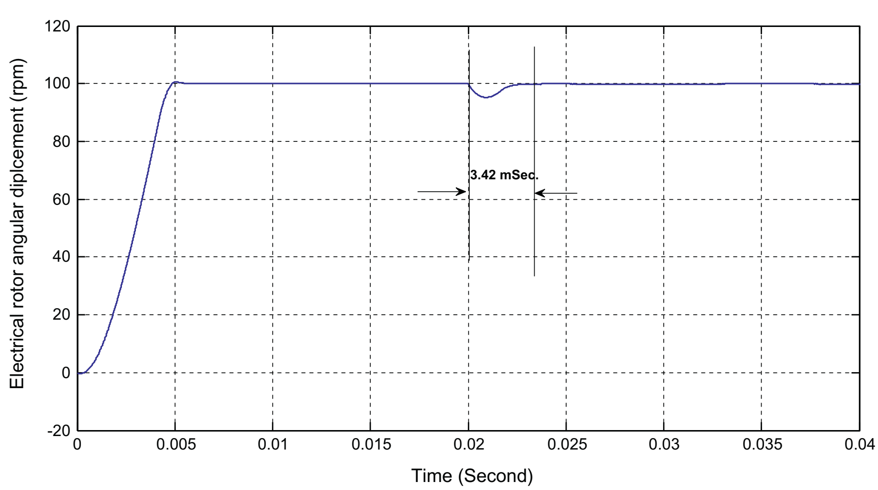

Figure 8 Effect of torque variation on the speed response using PSO.

$$j_{cc}(\theta,p(j,k,l)) = \sum_{i=1}^{s} j_{cc}(\theta,\theta^i(j,k,l))$$
$$= \sum_{i=1}^{s}\left[-d_{attractant}\exp\left(-\omega_{attractant}\sum_{m=1}^{p}(\theta_m-\theta_m^i)^2\right)\right]$$
$$+\sum_{i=1}^{s}\left[h_{reppelant}\exp\left(-\omega_{reppelant}\sum_{m=1}^{p}(\theta_m-\theta_m^i)^2\right)\right] \quad (9)$$

where $j_{cc}(\theta, p(j, k, l))$ is the objective function value to be added to the actual objective function (to be minimized) to present a time-varying objective function, s is the total number of bacteria, p is the number of variables to be optimized that are present in each bacterium, and $\theta = [\theta_1, \theta_2, ..., \theta_p]^T$ is a point in the p-dimensional search domain. $d_{attractant}$, $\omega_{attractant}$, $h_{repellant}$, $\omega_{repellant}$ are different coefficients that should be chosen properly.

6. Simulation results

Table 1 and Fig. 7 show step response parameters of the closed loop system with PSO–PID controller using ITSE based fitness function and without PSO–PID controller. Figs. 8 and 9 show the effect of torque variation from (1–4) N m on the speed response at (t = 0.02) s. by using PSO–PID controller where recovery time reaches the reference speed within (3.42 m s), recovery time reaches the (4 N m) within (3.1 m s).where:

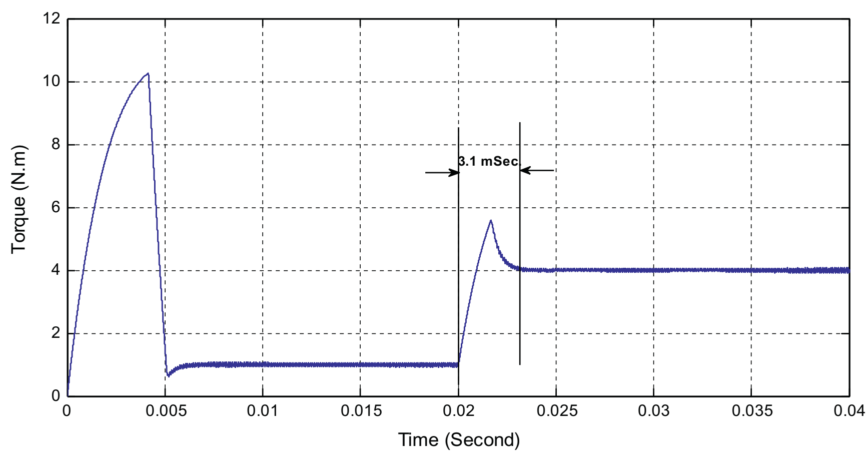

Figure 9 Effect of torque variation using PSO.

Table 2 BF-PID controller.

BF (PID) controller	K_p	K_i	K_d	Peak time (t_p)	Rise time (t_r)	Settling time (t_s)	Max. over shoot M_p %	Steady-state error e_{ss}
With	5.4936	0.9833	0.0034	0.0769	0.0030	0.0053	0	0.0561
Without	1	0	0	0.0055	0.0030	0.0163	13.956	0.5248

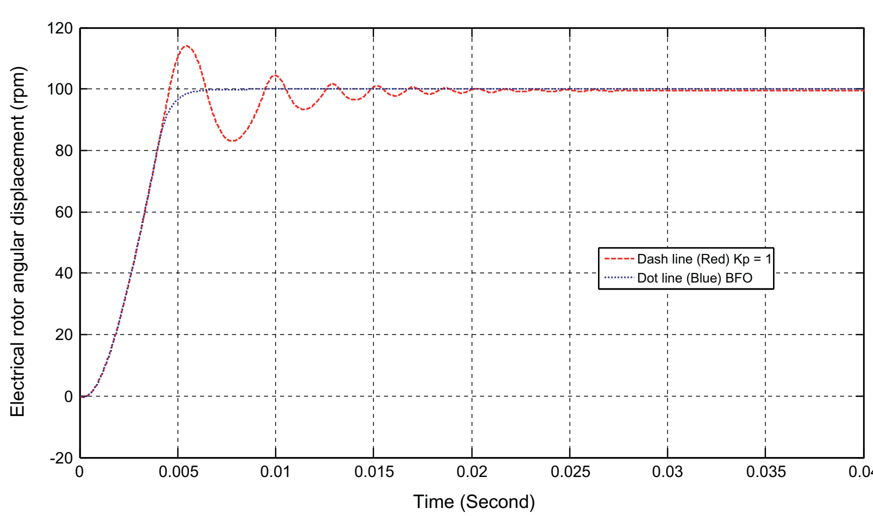

Figure 10 Step response of the closed loop system with BF-PID controller using ITSE based fitness function and without BF-PID controller.

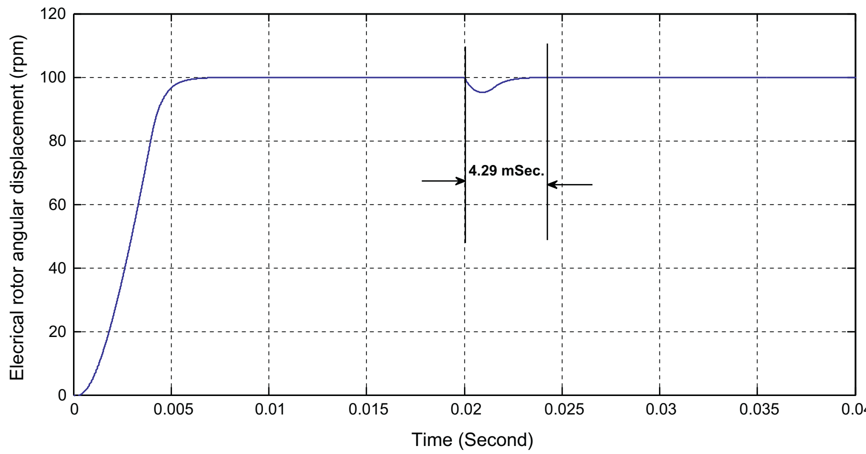

Figure 11 Effect of torque variation on the speed response using BF technique.

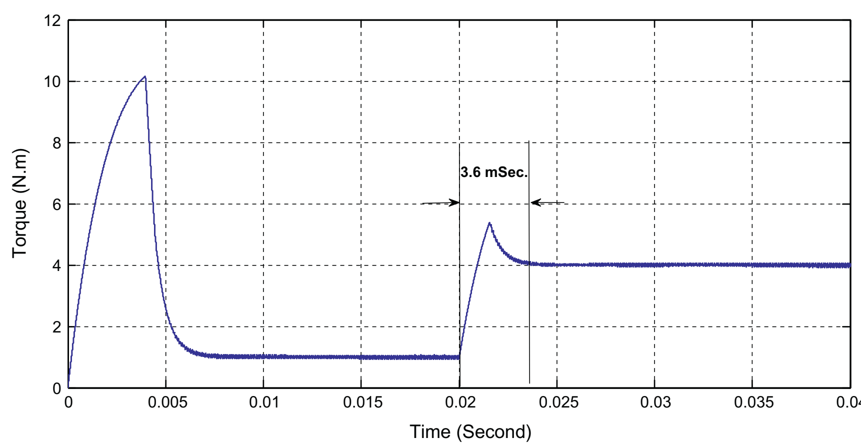

Figure 12 Effect of torque variation using BF technique.

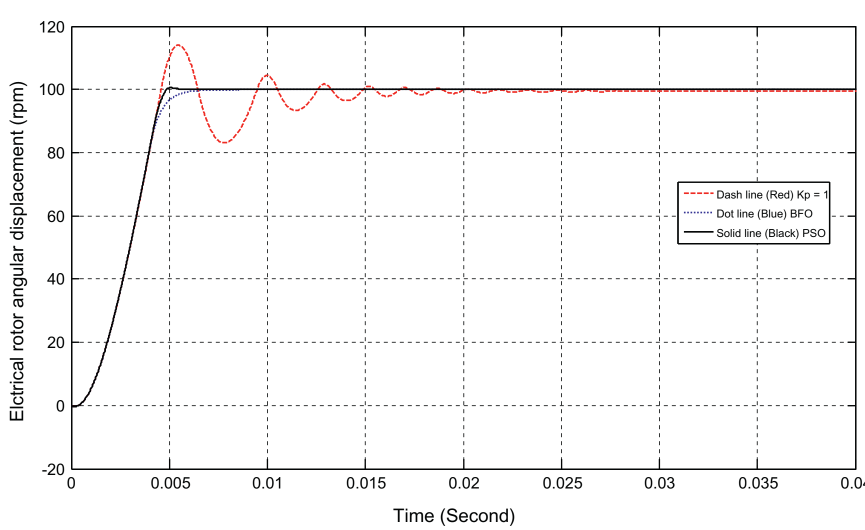

Figure 13 Step response of the closed loop system with (PSO, BF) PID controller using ITSE based fitness function and without (PSO, BF) PID controller.

- No. of iterations = 100, Swarm size = 50, correction factor = 2,
- Weighting factor = 1, ITSE (objective fitness function used with PSO) = $\int te^2 dt$.

Table 2 and Fig. 10 show step response parameters of the closed loop system with BF–PID controller using ITSE based fitness function and without BF–PID controller. Figs. 11 and 12 show the effect of torque variation from (1–4) N m on the speed response at (t = 0.02) s. by using BF–PID controller where recovery time reaches the reference speed within (4.29 m s), recovery time reaches the (4 N m) within (3.6 m s).where:

- p (Dimension of the search space) = 3, s (total number of bacteria) = 50,
- N_c(number of chemotactic steps) = 5, N_s (swimming length) = 4,
- N_{re} (number of reproduction steps) = 10,
- $c(i)$ Size of the step = 8.0e−007,
- N_{ed} (number of elimination-dispersal events) = 2
- p_{ed} (Elimination–dispersal probability) = 0.25.

Fig. 13 shows step response parameters of the closed loop system with (PSO, BF) PID controller using ITSE based fitness function and without (PSO, BF) PID controller.

7. Conclusion

In this work, a comparison study of using PSO and BFO methods for the tuning of PID controller for speed control of a BLDC motor. Obtained through simulation of BLDC motor, the simulation results show that the proposed controller can perform an efficient search for the optimal gains of PID controller. By comparing between PSO method and BF technique, it shows that PSO method can improve the dynamic performance of the system in a better way.

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