A PSO-Based Optimum Design of PID Controller for a Linear Brushless DC Motor

Mehdi Nasri, Hossein Nezamabadi-pour, and Malihe Maghfoori

Abstract—This Paper presents a particle swarm optimization (PSO) method for determining the optimal proportional-integral-derivative (PID) controller parameters, for speed control of a linear brushless DC motor. The proposed approach has superior features, including easy implementation, stable convergence characteristic and good computational efficiency. The brushless DC motor is modelled in Simulink and the PSO algorithm is implemented in MATLAB. Comparing with Genetic Algorithm (GA) and Linear quadratic regulator (LQR) method, the proposed method was more efficient in improving the step response characteristics such as, reducing the steady-states error; rise time, settling time and maximum overshoot in speed control of a linear brushless DC motor.

Keywords—Brushless DC motor, Particle swarm optimization, PID Controller, Optimal control.

I. INTRODUCTION

THERE are mainly two types of dc motors used in 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].

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 advantage of AC motor such as simple structure, higher reliability and free maintenance. In addition, brushless DC motor has the following advantages: smaller volume, high force, and simple system structure. So it is widely applied in areas which needs high performance drive [2].

From the control point of view, dc motor exhibit excellent control characteristics because of the decoupled nature of the field and armature mmf's [1]. Recently, many modern control methodologies such as nonlinear control [3], optimal control [4], variable structure control [5] and adaptive control [6] have been widely proposed for linear brushless permanent magnet DC motor. However, these approaches are either complex in theorical bases or difficult to implement [7]. PID control with its three term functionality covering treatment to both transient

and steady-states response, offers the simplest and yet most efficient solution to many real world control problems [8]. In spite of the simple structure and robustness of this method, optimally tuning gains of PID controllers have been quite difficult.

Yu *et al.* [9] have presented a LQR method to optimally tune the PID gains. In this method, the response of the system is near optimal but it requires mathematical calculation and solving equations. Lin *et al.* [10] have introduced GA-based PID control for brushless DC motor. Genetic algorithm is a stochastic optimization algorithm that is originally motivated by the mechanism of natural selection and evolutionary genetics.

Though the GA methods have been employed successfully to solve complex optimization problems, recent search has identified some deficiencies in GA performance. This degradation in efficiency is apparent in applications with highly *epistatic* objective functions (i.e., where the parameters being optimized are highly correlated), the crossover and mutation operations cannot ensure better fitness of offspring because chromosomes in the population have similar structure and their average fitness are high toward the end of the evolutionary process [11], [12], [13]. PSO first introduced by Kennedy and Eberhart is one of the modern heuristic algorithms, it has been motivated by the behavior of organisms, such as fish schooling and bird flocking [14]. Generally, PSO is characterized as a simple concept, easy to implement, and computationally efficient. Unlike the other heuristic techniques, PSO has a flexible and well-balanced mechanism to enhance the global and local exploration abilities [15].

In this paper, a novel PSO-based approach to optimally design a PID controller for a brushless DC motor is proposed. This paper has been organized as follows: in section 2 the linear brushless DC motor is described and the speed model of it is shown. In section 3, the particle swarm optimization method is reviewed. Section 4, describes how PSO is used to design the PID controller optimally for a linear brushless DC motor. A comparison between the results obtained by the proposed method and GA method and LQR design [9] via simulation the DC motor is presented in section 5. The paper is concluded in section 6.

II. LINEAR BRUSHLESS DC MOTOR

Permanent magnet DC motors use mechanical commutators and brushes to achieve the commutation. However, BLDC motors adopt Hall Effect sensors in place of mechanical commutators and brushes [17]. The stators of BLDC motors are the coils, and the rotors are the permanent magnets. The

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stators develop the magnetic fields to make the rotor rotating. Hall Effect sensors detect the rotor position as the commutating signals. Therefore, BLDC motors use permanent magnets instead of coils 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. The dynamic characteristics of BLDC motors are similar to   permanent magnet   DC motors.   The characteristic equations of BLDC motors can be represented as [18]:

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

$$v_{emf} = K_b.\omega(t) \qquad (2)$$

$$T(t) = K_t.i(t) \qquad (3)$$

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

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 the resistance of the stator, $v_{emf}(t)$ 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, and K_b is the back electromotive force constant.

Fig. 1 shows the block diagram of the BLDC motor. From the characteristic equations of the BLDC motor, the transfer function of speed model is obtained

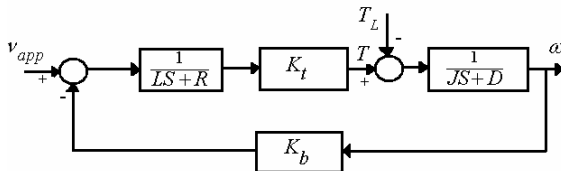$$\frac{\omega(s)}{v_{app}(s)} = \frac{K_t}{LJ.S^2 + (LD + RJ)S + K_t K_b} \qquad (5)$$

Fig. 1 The block diagram of BLDC motor

The parameters of the motor used for simulation are as follows:

TABLE I
PARAMETERS OF THE MOTOR

Parameters	Values and units
R	21.2 Ω
K_b	0.1433 Vs rad^{-1}
D	$1*10^{-4}$ Kg-m s/rad
L	0.052 H
K_t	0.1433 Kg-m/A
J	$1*10^{-5}$ Kgm s^2/rad

III.   OVERVIEW OF PARTICLE SWARM OPTIMIZATION

PSO is one of the optimization techniques and a kind of evolutionary computation technique. The method has been found to be robust in solving problems featuring nonlinearity and nondifferentiability, multiple optima, and high dimensionality through adaptation, which is derived from the social-psychological theory [13]. The technique is derived from research on swarm such as fish schooling and bird flocking. According to the research results for a flock of birds, birds find food by flocking (not by each individual). The observation leads the assumption that every information is shared inside flocking. Moreover, according to observation of behavior of human groups, behavior of each individual (agent) is also based on behavior patterns authorized by the groups such as customs and other behavior patterns according to the experiences by each individual. The assumption is a basic concept of PSO [16]. In the PSO algorithm, instead of using evolutionary operators such as mutation and crossover, to manipulate algorithms, for a d-variabled optimization problem, a flock of particles are put into the d-dimensional search space with randomly chosen velocities and positions knowing their best values so far (Pbest) and the position in the d-dimensional space. The velocity of each particle, adjusted according to its own flying experience and the other particle's flying experience. For example, the i th particle is represented as $x_i = (x_{i,1}, x_{i,2},..., x_{i,d})$ in the d-dimensional space. The best previous position of the i th particle is recorded and represented as:

$\text{Pbest}_i = (\text{Pbest}_{i,1}, \text{Pbest}_{i,2},..., \text{Pbest}_{i,d})$.

The index of best particle among all of the particles in the group is gbest_d . The velocity for particle i is represented as $v_i = (v_{i,1}, v_{i,2},...., v_{i,d})$. The modified velocity and position of each particle can be calculated using the current velocity and the distance from $\text{Pbest}_{i,d}$ to gbest_d as shown in the following formulas [13]:

$$v_{i,m}^{(t+1)} = w.v_{i,m}^{(t)} + c_1 * rand() * (pbest_{i,m} - x_{i,m}^{(t)})$$
$$+ c_2 * Rand() * (gbest_m - x_{i,m}^{(t)}) \quad (6)$$

$$x_{i,m}^{(t+1)} = x_{i,m}^{(t)} + v_{i,m}^{(t+1)} \quad (7)$$
$$i = 1,2,...,n$$
$$m = 1,2,...,d$$

where

n	Number of particles in the group
d	dimension
t	Pointer of iterations(generations)
$v_{i,m}^{(t)}$	Velocity of particle I at iteration t $V_d^{min} \leq v_{i,d}^{(t)} \leq V_d^{max}$
w	Inertia weight factor
c_1, c_2	Acceleration constant
$rand()$ $Rand()$	Random number between 0 and 1
$x_{i,d}^{(t)}$	Current position of particle i at iterations
$Pbest_i$	Best previous position of the ith particle
$gbest$	Best particle among all the particles in the population

IV. IMPLEMENTATION OF PSO-PID CONTROLLER

A. Fitness Function

In PID controller design methods, the most common performance criteria are integrated absolute error (IAE), the integrated of time weight square error (ITSE) and integrated of squared error (ISE) that can be evaluated analytically in the frequency domain [19], [20]. These three integral performance criteria in the frequency domain have their own advantage and disadvantages. For example, disadvantage of the *IAE* and *ISE* criteria is that its minimization can result in a response with relatively small overshoot but a long settling time because the *ISE* performance criterion weights all errors equally independent of time. Although the *ITSE* performance criterion can overcome the disadvantage of the *ISE* criterion, the derivation processes of the analytical formula are complex and time-consuming [21]. The *IAE*, *ISE*, and *ITSE* performance criterion formulas are as follows:

$$IAE = \int_0^\infty |r(t) - y(t)| dt = \int_0^\infty |e(t)| dt \quad (8)$$

$$ISE = \int_0^\infty e^2(t) dt \quad (9)$$

$$ISTE = \int_0^\infty te^2(t) dt \quad (10)$$

In this paper a time domain criterion is used for evaluating the PID controller [13]. A set of good control parameters P, I and D can yield a good step response that will result in performance criteria minimization in the time domain. These performance criteria in the time domain include the overshoot, rise time, settling time, and steady-state error. Therefore, the performance criterion is defined as follows [13]:

$$\min_{K:stablizing} W(K) = (1 - e^{-\beta}).(M_p + E_{ss}) + e^{-\beta} \quad (11)$$
$$.(t_s - t_r)$$

Where K is [P, I, D], and β is the weightening factor. The performance criterion W(K) can satisfy the designer requirement using the weightening factor β value. β can set to be larger than 0.7 to reduce the overshoot and steady states error, also can set smaller than 0.7 to reduce the rise time and settling time [13]. The optimum selection of β depends on the designer's requirement and the characteristics of the plant under control. In BLDC motor speed control system the lower β would lead to more optimum responses. In this paper, due to trials, β is set to 0.5 to optimum the step response of speed control system.

The fitness function is reciprocal of the performance criterion, in the other words:

$$f = \frac{1}{W(K)} \quad (12)$$

B. Proposed PSO-PID Controller

In this paper a PSO-PID controller used to find the optimal parameters of LBDC speed control system.

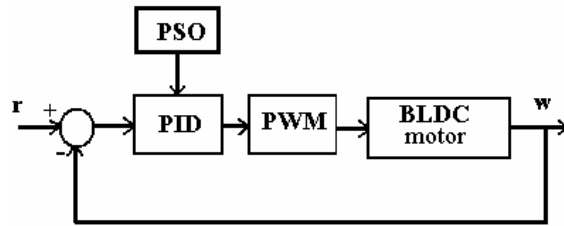Fig. 2 shows the block diagram of optimal PID control for the BLDC motor.

Fig. 2 Optimal PID control

In the proposed PSO method each particle contains three members P, I and D. It means that the search space has three dimension and particles must 'fly' in a three dimensional space.

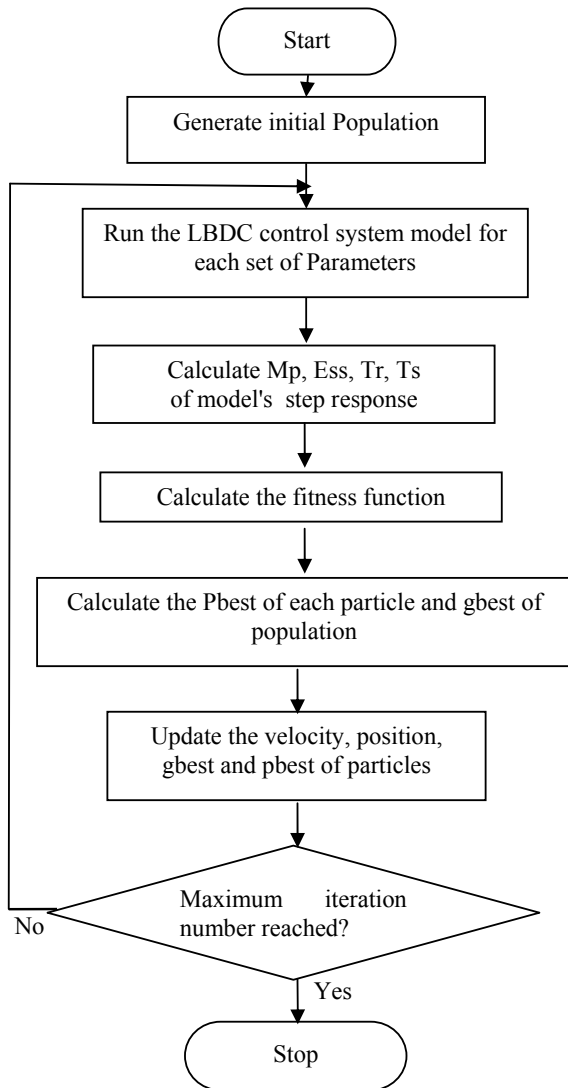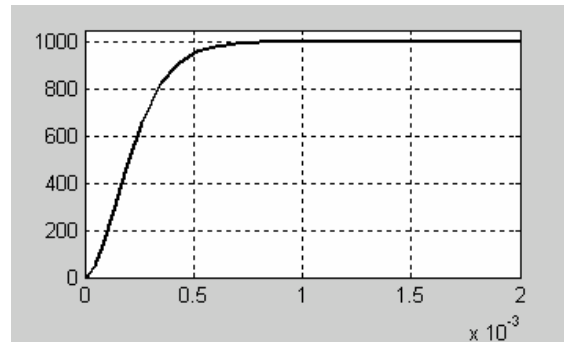The flow chart of PSO-PID controller is shown in Fig. 3.

Fig. 4 Step response of BLDC motor in PSO based PID speed control

Table II lists the performance of the PSO-PID controller.

TABLE II
PERFORMANCE OF THE PSO-PID CONTROLLER

| [P I D]	[190.0176,50,0.039567]
Rise time(ms)	0.3038
Max overshoot (%)	0
Steady States error	0.77186
Settling time(ms)	0.60116

Fig. 5 shows the convergence graph in the PSO method.

Fig. 5 Convergence graph in the PSO method

Fig. 3 Flowchart of the PSO-PID Control system

V. NUMERICAL EXAMPLES AND RESULTS

A. Optimal PSO-PID Response

To control the speed of the LBDC motor at 1000 rmp, according to the trials, the following PSO parameters are used to verify the performance of the PSO-PID controller parameters:

- Population size: 20;
- $w_{max} = 0.6, w_{min} = 0.1$;
- $C_1 = C_2 = 1.5$;
- Iteration :20;

The optimal PID controller is shown in Fig. 4.
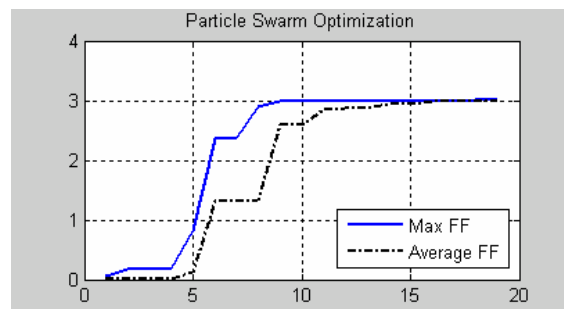
B. Comparison of PSO-PID Method with LQR and GA Methods

To show the effectiveness of the proposed method, a comparison is made with the designed PID controller with GA and LQR methods. At first method, the PID controller is designed using LQR method [9] and the values of designed PID Controller are 70.556, 10, and 0.0212 [9]. Also, GA method is used to tune the PID controller. The following GA parameters which are used to verify the performance of the GA-PID controller parameters:

- Population size: 30
- Crossover rate: 0.9
- Mutation rate: 0.005
- Number of iterations :30

The values of designed PID Controller are 93.1622, 38.6225, and 0.027836. Fig. 6 shows the convergence graph in the GA method, Fig. 7 shows the PSO response in comparison with

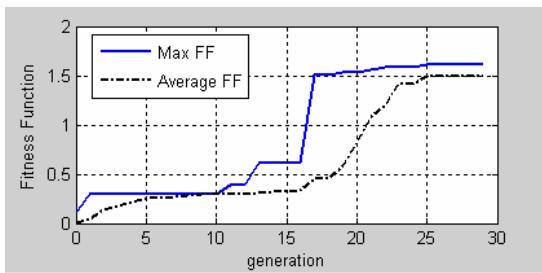GA and LQR methods and Table III lists the performance of the two methods.

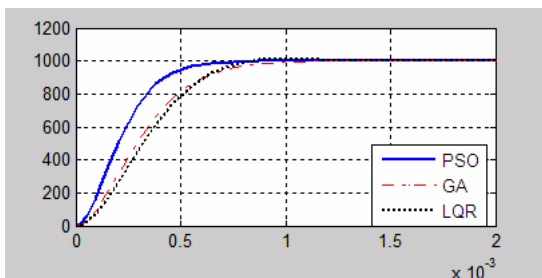Fig. 6 Convergence graph in the GA method

Fig. 7 Comparison between GA, LQR and PSO based PID control in speed control of LBDC motor

TABLE III
LQR AND GA PERFORMANCE

	LQR	GA
P	70.556	93.1622
I	10	38.6225
D	0.0212	0.027836
Tr (ms)	0.46786	0.46127
Mp%	1.4186	0
Ess	2.2513	1.5785
Ts (ms)	0.79368	0.87404

VI. CONCLUSION

In this paper a new design method to determine PID controller parameters using the PSO method is presented. Obtained through simulation of BLDC motor, the results show that the proposed controller can perform an efficient search for the optimal PID controller. By comparison with LQR and GA methods, it shows that this method can improve the dynamic performance of the system in a better way.

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