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Soft Computing Based Design of PID Controller for a Linear Brushless DC Motor

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Abstract: This study 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 modeled 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.

Key words: Brushless DC motor, particle swarm optimization, PID controller, optimal control, Genetic Algorithm (GA)

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 (Hambley, 1997). 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 (Kennedy and Eberhart, 1995). From the control point of view, DC motor exhibit excellent control characteristics because of the decoupled nature of the field and armature mmf's (Hambley, 1997). Recently, many modern control methodologies such as nonlinear control (Ong, 1997), optimal control (Jones, 1967), variable structure control (Bhimbra, 1993) and adaptive control have been widely proposed for linear brushless permanent magnet DC motor. However, these approaches are either complex in theoretical bases or difficult to implement. 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. In spite of the simple structure and robustness of this method, optimally tuning gains of PID controllers have been quite difficult. 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 (Deb, 2002).

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 (Gen and Cheng, 2002).

The stators of BLDC motors are the coils and the rotors are the permanent magnets. The 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 study, 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

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characteristics of BLDC motors are similar to permanent magnet DC motors. The characteristic equations of BLDC motors can be represented as (Hambley, 1997) follows:

$$V_{app}(t) = L\,d\,i\,(t)/dt + R.i\,(t) + v_{emf}\,(t) \quad (1)$$

$$V_{emf} = K_b\,\omega\,(t) \quad (2)$$

$$T\,(t) = K_t.i\,(t) \quad (3)$$

$$T\,(t) = J\,d\,\omega\,(t)/dt + D.\,\omega\,(t) \quad (4)$$

Where:

V_{app} (t)	=	The applied voltage
ω (t)	=	The motor speed
L	=	The inductance of the stator
i (t)	=	The current of the circuit
R	=	The resistance of the stator
emf (t)	=	The back electromotive force
T	=	The torque of motor
D	=	The viscous coefficient
J	=	The moment of inertia
K_t	=	The motor torque constant
K_b	=	The back electromotive force constant

Figure 1 shows the block diagram of the BLDC motor. From the characteristic equations (Deb, 2002) of the BLDC motor, the transfer function of speed model is obtained the parameters of the motor used for simulation are as follows (Table 1):

$$\omega\,(s)/V_{app}\,(s) = K_t/(\,L.J.S^2 + (LD + RJ)\,S + K_tK_b) \quad (5)$$

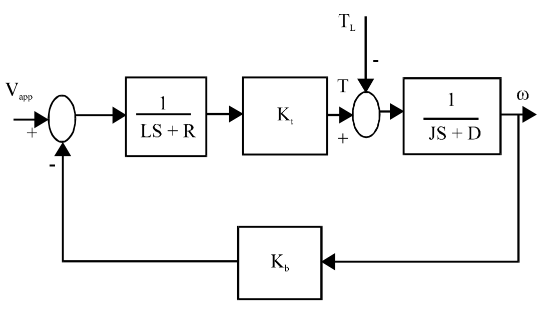

Fig. 1: The block diagram of BLDC motor

Table1: The parameters of the motor used for simulation

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

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 no differentiability, multiple optima and high dimensionality through adaptation which is derived from the Social-Psychological Theory (Rao, 1984). 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 (Krishnan, 2001). The velocity of each particle, adjusted according to its own flying experience and the other particle's flying experience (Satakshi *et al*., 2005). For example, the ith particle is represented as $x_i = (x_{i,1}, x_{i,2},..., x_{i,d})$ in the d-dimensional space (Mukherjee *et al*., 2004). The best previous position of the ith particle is recorded and represented as:

$$V_i\,(t+1) = W_iV_i\,(t) + C_1rand\,(Pbest_i - X_i\,(t)) + C_2rand\,(gbest - X_i\,(t))$$

$$X_i\,(t+1) = X_i\,(t) + V_i\,(t)$$

$$w = w_{Max} - [(w_{Max} - w_{Min})\,iter]/\,max_{Iter}$$

Where:

V_i (t)	=	Current velocity of agent i at iteration t
V_i (t+1)	=	Modified velocity of agent i
X_i (t)	=	Current position of agent i at iteration t
W_{max}	=	Initial weight
W_{min}	=	Final weight
max_{Iter}	=	Maximum iteration number
iter	=	Current iteration number

IMPLEMENTATION OF PSO-PID CONTROLLER

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. 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 (Eberhart and Kennedy, 1995) 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 (Nagaraj *et al*., 2008):

- Integral of Absolute Error (IAE) = $\int$ e (t).dt
- Integral of Squared Error (ISE) = $\int$ {e (t)}^{2}.dt
- Integral of Time multiplied by Absolute Error (ITAE) = $\int$ t e (t).dt
- Integral of Time Multiplied by Squared Error (ITSE) = $\int$ t{e(t)}^{2}.dt

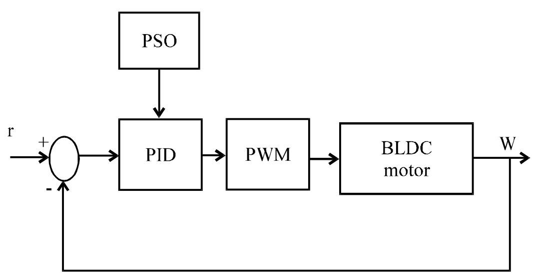

Fig. 2: Optimal PID control

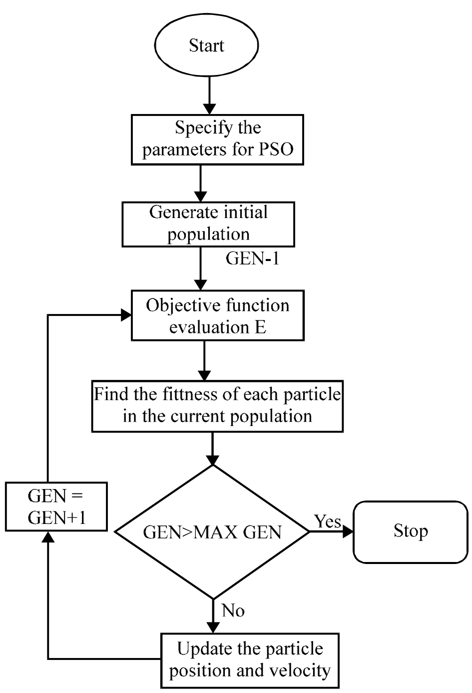

Fig. 3: Flow chart of the PSO-PID Control System

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

$$f = 1/W\ (K)$$

Proposed PSO-PID controller: In this study, a PSO-PID controller used to find the optimal parameters of LBDC speed control system. Figure 2 shows the block diagram of optimal PID control for the BLDC motor. 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.

NUMERICAL EXAMPLES AND RESULTS

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; C1 = C2 =1.5 and Iteration: 20 (Table 2). The optimal PID controller is shown in Fig. 4.

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 (Fig. 5). At first method, the PID controller is designed using LQR Method

Table 2: The performance of the PSO-PID controller

Performance (PID)	Values (190.0176,50,0.039567)
Rise time (msec)	0.30380
Max overshoot (%)	0.00000
Steady states error	0.77186
Settling time (msec)	0.60116

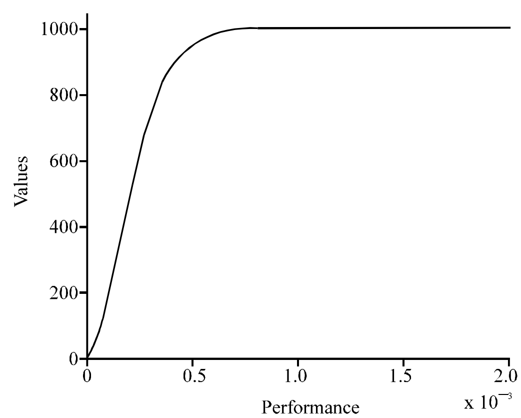

Fig. 4: Step response of BLDC motor in PSO based PID speed control

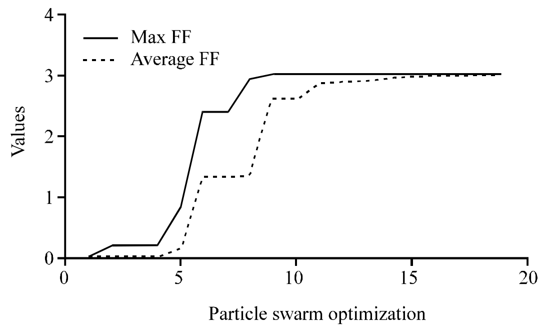

Fig. 5: The convergence graph in the PSO Method

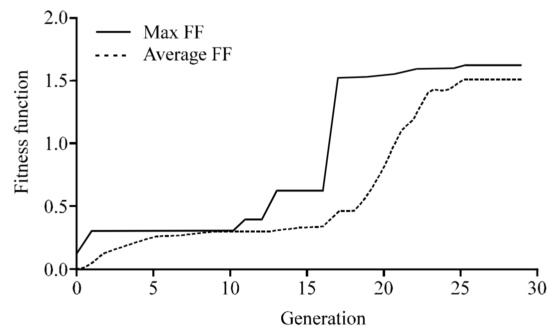

Fig. 6: Convergence graph in the GA Method

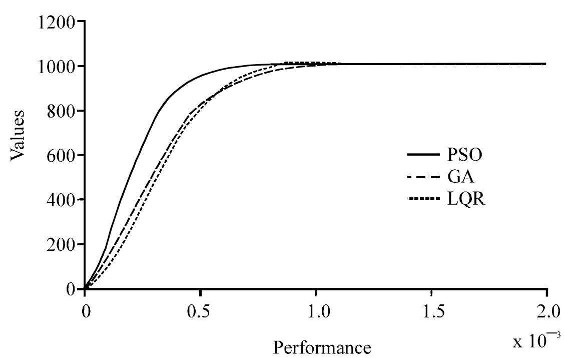

Fig. 7: Comparison between GA, LQR and PSO based PID control in speed control of LBDC motor

and the values of designed PID controller are 70.556,10 and 0.0212. 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 and No. of iterations: 30.

The values of designed PID Controller are 93.1622, 38.6225 and 0.027836. Figure 6 shows the convergence g raph in the GA Method, Fig. 7 shows the PSO response in comparison with GA and LQR Methods and Table 3 shows the performance of the two methods.

Table 3: LQR, GA and PSO performance

Parameters	LQR	GA	PSO
P	70.556	93.1622	190.0176
I	10	38.6225	50
D	0.0212	0.027836	0.039567
Tr (msec)	0.46786	0.46127	0.3038
MP (%)	1.4186	0	0
Ess	2.2513	1.5785	0.77186
Ts (msec)	0.79368	0.87404	0.60116

CONCLUSION

In this study, 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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