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OPTIMUM TUNING OF PID CONTROLLER FOR A PERMANENT MAGNET BRUSHLESS MOTOR

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Abstract: **The proportional-integral-derivative (PID) controllers were the most popular controllers of this century because of their remarkable effectiveness, simplicity of implementation and broad applicability. However, PID controllers are poorly tuned in practice with most of the tuning done manually which is difficult and time consuming. The computational intelligence has purposed genetic algorithms (GA) and particle swarm optimization (PSO) as opened paths to a new generation of advanced process control. The main objective of these techniques is to design an industrial control system able to achieve optimal performance when facing variable types of disturbances which are unknown in most practical applications. This paper presents a comparison study of using two algorithms for the tuning of PID-controllers for speed control of a Permanent Magnet Brushless DC (BLDC) Motor. The PSO has superior features, including easy implementation, stable convergence characteristic and good computational efficiency. The BLDC Motor is modelled using system identification toolbox. Comparing GA with PSO method proves that the PSO was more efficient in improving the step response characteristics. Experimental results have been investigated to show their agreement with simulation one.**

Keywords— Permanent Magnet Brushless DC (BLDC) Motor, Particle Swarm Optimization (PSO), Genetic Algorithm (GA), PID Controller, and Optimal control.

1. INTRODUCTION

The usefulness of PID controllers lies in their general applicability to most control systems. The PID controller is a combination of PI and PD controllers. It is a lag-lead-lead compensator. Note that the PI control and PD control actions occur in different frequency regions. The PI control action occurs at the low-frequency region and the PD control action occurs at the high-frequency region. The PID control may be used when the system requires improvement in both transient and steady-state performances

Figure 1 shows a PID control of a plant G(s). If the mathematical model of the plant can be derived, then it is possible to apply various design techniques for determining the parameters of the controller that will meet the transient and steady-state specifications of the closed loop system.

Ziegler and Nichols suggested rules for tuning PID controllers based on experimental step responses in process control system where the plant dynamics are precisely known. Over many years such tuning techniques proved to be useful. In order to optimize the PID controller parameters, the PSO and GA have been used to optimize PID parameters.

PSO shares many similarities with evolutionary computation techniques such as GA. the performance of the BLDC Motor with the PID controller tuned by GA is compared with the same controller tuned by PSO using different objective functions [1], [2], [3].

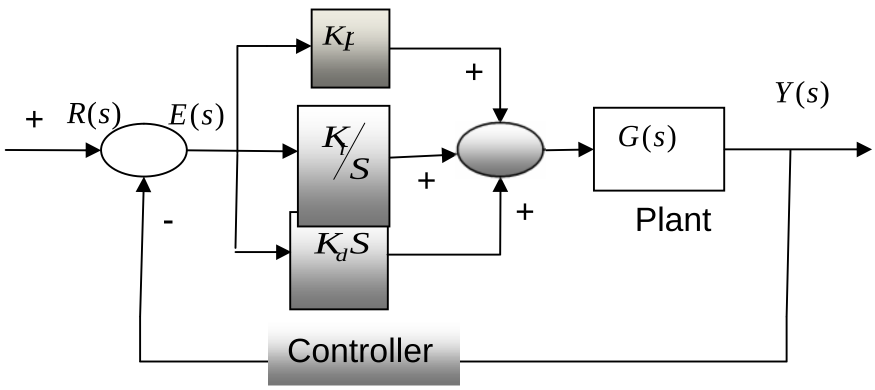

Figure 1: PID Controlled System.

This paper is restricted for considering the two aforementioned optimization algorithms, PSO and GA, for tuning the gains of PID controllers that is used with the BLDC Motor. This is done by presenting some results obtained by using each algorithm individually. These results are compared and relative merits of these algorithms are discussed.

2. SYSTEM MODELLING

2.1. PID Controller and Fitness Function Modelling

The PID controller has been widely adopted as the control strategy in the production process. Basically, a proportional-plus-integral-plus-derivative (PID) controller will improve the speed of the response, the steady-state error, and the system stability. However, the setting of PID parameters is related to the characters of system process. Thus, the proper or optimum PID parameters are needed to approach the desired performance. The transfer function of a PID controller is [1].

$$G_c(s) = K_p + \frac{K_d}{S} + K_d S \tag{1}$$

The strategies of PSO and GA are implemented for the optimum search of the controller parameters. These done according to the criteria of performance index, i.e., IAE (Integral

Absolute-Error), ISE (Integral Square-Error), ITAE (Integral of Time multiplied by Absolute Error), WGAM1 (Weighted Goal Attainment Method 1), and WGAM2 (Weighted goal attainment method 2 (WGA2).The three integral performance criteria in the frequency domain have their own advantages and disadvantages [4]. The IAE, ISE, ITSE, WGAM1, and WGAM2 performance criterion formulas are described by equations 2, 4, 5, 6, and 7 respectively.

$$IAE = \int_0^\infty |r(t) - y(t)| dt = \int_0^\infty |e(t)| dt \tag{2}$$

Then the fitness function (*f*) to be maximized using IAE is given by equation (3).

$$f = \frac{1}{IAE} \tag{3}$$

$$ISE = \int_0^\infty [e(t)]^2 \, dt \tag{4}$$

$$ITAE = \int_0^\infty t |e(t)| dt \tag{5}$$

$$WGAM1 = \frac{1}{[c_1(t_r - t_{rd})^2 + c_2(M_p - M_{pd})^2 + c_3(t_s - t_{sd})^2 + c_4(e_{ss} - e_{ssd})^2]} \tag{6}$$

$$WGAM2 = \frac{1}{(1 - e^{-\beta}) \cdot (M_p + e_{ss}) + (e^{-\beta}) \cdot (t_s - t_r)} \tag{7}$$

Where, *r(t)* is the desired output, *y(t)* is the plant output, *e(t)* is the error signal, β weighting factor, $c_1 : c_4$ are positive constants (weighting factor), their values are chosen according to prioritizing their importance, t_{rd} is the desired rise time, M_{pd} is the desired maximum overshoot, t_{sd} is the desired settling time, and e_{ssd} is the desired steady state error.

2.2. Permanent Magnet Brushless DC Motor Modelling

In this section, system identification toolbox in MATLAB used to find the transfer function of the motor and its drive circuit. The state space models are estimated for orders ranging from 1 to 5 ($n_a = 1{:}5$) using descending step input voltage data (5-2 V) and its related output as a test data. The same set of data is used as a validation data and time delay of 0.03 sec for all models. Figure (2) shows the measured output and the percentage fit of each model to the measured output. It is clear from figure (2) that the best fitting for the validation data set is obtained for state space model of order three (94.08%) [5]. Then, the transfer function of the motor and its drive circuit is indicated in equation 8, the closed loop system is as shown in Figure (3).

$$G_p(S) = \frac{312.3S + 1.7774e4}{S^2 + 10.2S + 54.32} \tag{8}$$

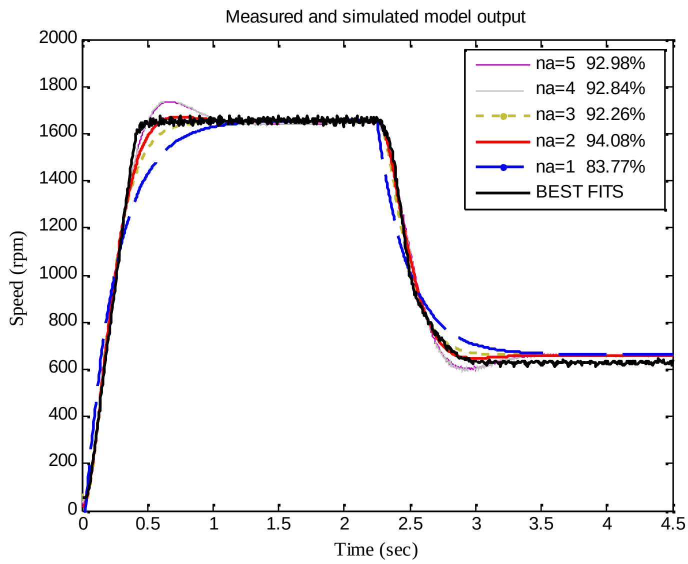

Figure 2: Measured and simulated state space model output

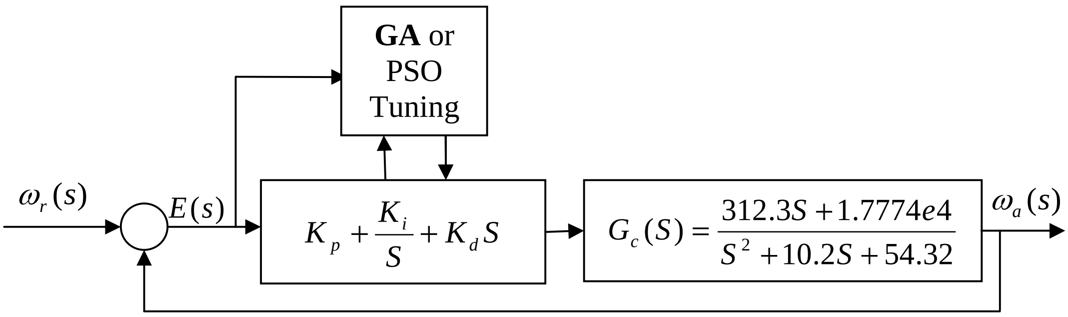

Figure 3: The structure of GA or PSO of PID tuning system.

2.3. Modelling of the PSO-PID Controller

In this section, the PSO-PID controller is proposed. The method of tuning the parameters of PID controller by the PSO is studied. The operation algorithm is based on the local and global best solution as the following equations [1], [2].

$$v_i^{k+1} = w_i v_i^k + c_1 randx(pbest_i - s_i^k) + c_2 rand(gbest - s_i^k) \quad (9)$$

Where, v_i^k is the current velocity of particle i at iteration k, v_i^{k+1} is the updated velocity of particle i, w_i is the different inertia weight of particle i, c_1 and c_2 are acceleration positive constants, s_i^k is the current position of particle i at iteration k, rand is random number between 0 and 1, $pbest_i$ is the best previous position of the i-th particle, and $gbest$ is the best particle among all the particles in the population.

Therefore the new position can be modified using the present position and updated velocity as in the next equation.

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (10)$$

The acceleration positive constants c_1 and c_2 are set to 2 [6]. The inertia weight w_i is set within the range (0.4 to 0.9) [7], [8].

2.4. Modelling of the GA-PID Controller

In this section, the GA-PID controller is proposed for comparison. The parameters of PID controller are tuned by the GA. In nature, evolution is mostly determined by natural selection, where individuals that are better are more likely to survive and propagate their genetic material. The encoding of genetic information (genome) is done in a way that admits reproduction which results in offspring or children that are genetically identical to the parent.

Reproduction allows some exchange and re-ordering of chromosomes, producing offspring that contain a combination of information from each parent. This is the recombination operation, which is often referred to as crossover because of the way strands of chromosomes crossover during the exchange. Diversity in the population is achieved by mutation. A typical GA procedure takes the following steps:

A population of candidate solutions (for the optimization task to be solved) is initialized. New solutions are created by applying genetic operators (mutation and crossover). The fitness of the resulting solutions is evaluated and suitable selection strategy is then applied to determine which solutions will be maintained into the next generation. The procedure is then iterated until a terminating criterion is achieved [1], [9].

3. SIMULATION AND EXPERIMENTAL RESULTS

3.1. Simulation Results

In the simulation, the optimum PID parameters are searched for the transfer function of the identified model with respect to the criteria of performance indices presented in equations 2, 4, 5, 6 and 7. The GAM1 searched for case1 (t_{rd} = 0.3, c_1=1 and $c_2 = c_3 = c_4 = 0$) and case3 (M_p = 0, t_{rd} = 0.3, c_1=0.1, c_2= 0.9 and c_3 = c_4= 0). The GAM2 searched for case1 ($\beta = 0.1$) and case2 ($\beta = 0.7$).The efforts of the identified model with the PSO and GA controllers are collected in. Table1. In addition, the time responses are shown in Figures 4, 5, and 6.

Table 1: The efforts of the PSO and GA for PID controllers in simulation

response &P,I,D values	Tuning methods	w.r.t. IAE	w.r.t. ISE	w.r.t. ITAE	w.r.t. WGAM1		w.r.t. WGAM2	
					Case1	Case2	Case1	Case2
value of fitness function	GA	3.9489	13.3110	17.1350	4.4e3	1.1e+04	2.6753	9.9592
	PSO	3.9512	13.3099	21.4743	4.4e3	1.6e+04	6.8187	11.3544
seeking time(sec)	GA	271	266	352	390	410	390	380
	PSO	94	67	140	240	249	286	265

rising time(sec)	GA	0.1400	0.1400	0.42	0.315	0.33	0.350	0.395
	PSO	0.1400	0.1400	0.415	0.3150	0.3250	0.520	0.53
overshot percentage	GA	0.4104	0.31	2.4301	20.81	0	2.9543	1.2034
	PSO	0	0.2955	0.2697	19.2549	0	1.9783	0.7255
settling time (sec)	GA	2.350	2.355	1	1.96	1.235	0.76	0.585
	PSO	2.350	2.355	0.645	1.5350	1.2200	0.520	0.53
Steady-state error	GA	0. 22	0. 22	7.74e-8	-0.0038	6.434e-4	5.1810e-6	2.5883e-9
	PSO	0.2156	0.2170	2.50e-7	0.0012	0	2.306e-06	1.1541e-7
P	GA	0.0090	0.009	0.002	1.9949e-5	0.0027	0.0012	0.0018
	PSO	0.0090	0.009	0.0023	0.00009	0.0027	0.0012824	0.0014399
I	GA	0.012	0.012	0.012	0.012	0.0119	0.012	0.012
	PSO	0.012	0.012	0.012	0.012	0.012	0.011923	0.011979
D	GA	0	2.7785e-6	3.220e-4	6.764e-6	6.0274e-6	4.6979e-5	5.371e-5
	PSO	1.3171e-5	3.2151e-6	3.027e-4	0	0	4.0973e-5	2.0459e-4

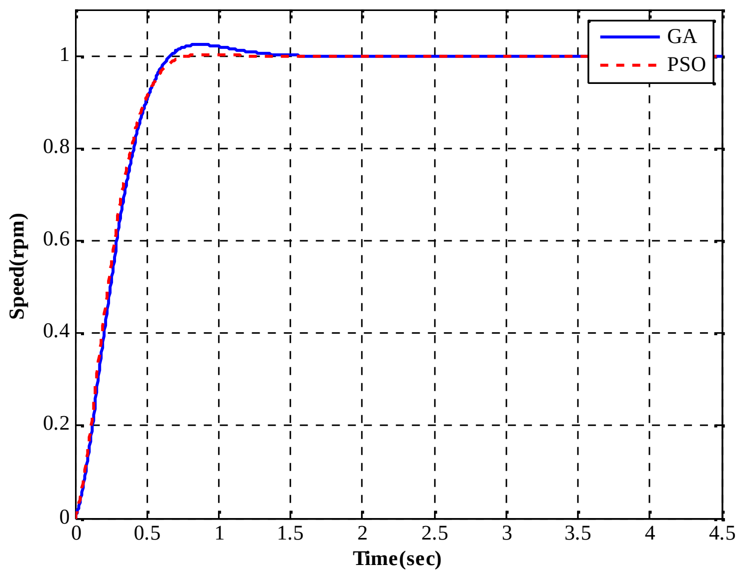

Figure 4: Simulation with respect to ITAE

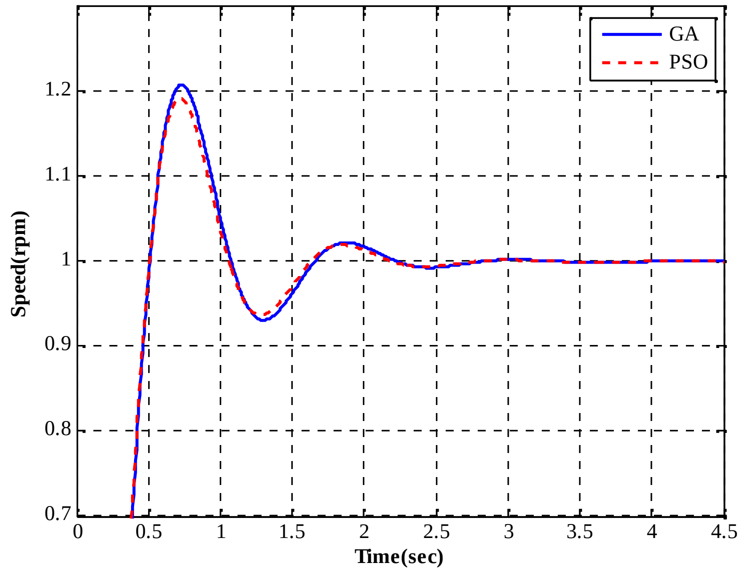

Figure 5: Simulation with respect to WGAM1case1

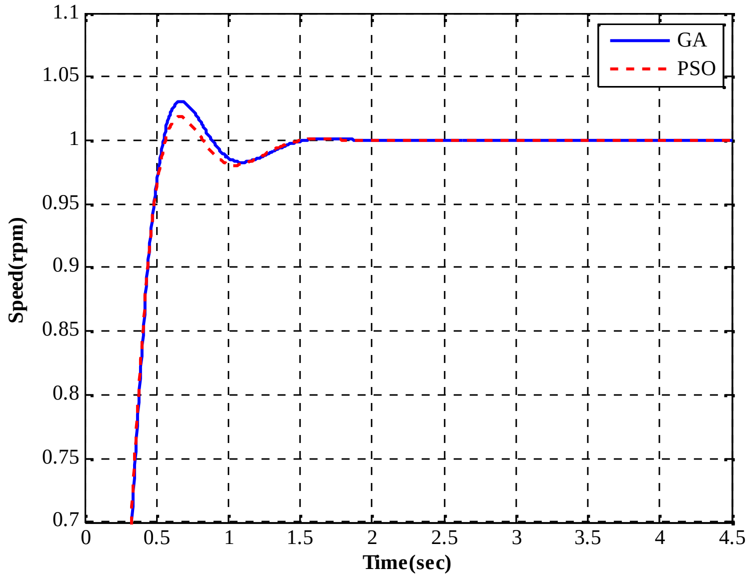

Figure 6: Simulation with respect to WGAM2 (case2)

3.2. Experimental results

The experiment was set up as shown in Figure (13). The parameters of tested BLDC Motor are listed in table (2). A data acquisition card (NI6014) was utilized as a control core responsible for the system control. The optimum PID controller tuned by GA and PSO using ITAE index is applied to closed-loop control of BLDC motor and its drive circuit. The experimental results of the practical system are compared with the simulation results of the same system under the influence of the same controller. Figure (7) illustrates the practical BLDC motor and the corresponding identified model performance with optimum PID controller tuned by PSO using the ITAE fitness function. Table (3) summarizes the steady state response of the practical BLDC motor and the corresponding identified model. It is clear from figure (7) and table (3) that the practical motor behaves like the identified model but the remarkable difference in the overshot is due to the output signal ripples in the practical model. The time responses of GA-PID and PSO-PID in the practical system are shown in Figures (8). Obviously, the PSO-PID controller has better performance and efficiency than the GA-PID controller.

Table 2: The parameters of Tested BLDC Motor

Power	370 W	Armature inductance (La)	8.5 mH
Speed	2000 rpm	Moment of inertia (J)	0.0008 kg.m2
Voltage	220 V	Coefficient of friction (B)	0.0003 N.m.sec/rad
Number of poles	4	EMF constant (Kb)	0.175 V.sec
Armature resistance (Ra)	2.8750 Ω		

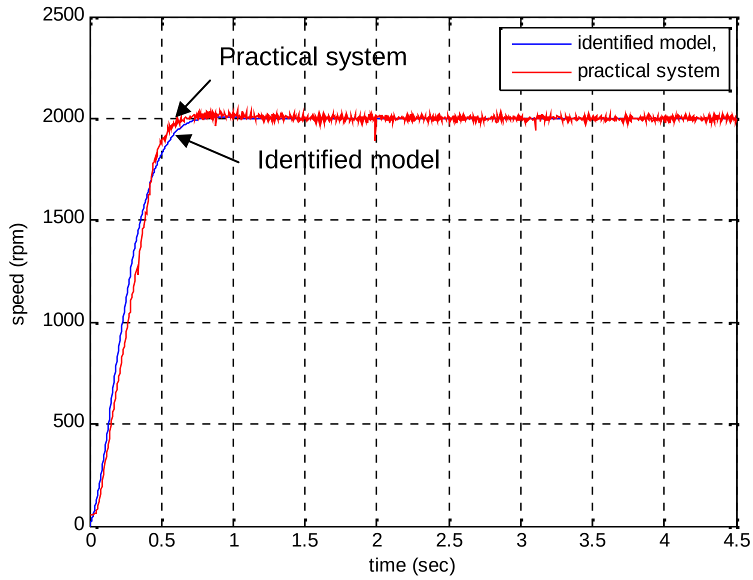

Figure 7: The speed response of practical motor and the identified model

Table 3: The steady-state response parameters using PSO-PID

Parameter	Actual System	Identified Model
Maximum over shoot Mp%	2.0813%	0.2711%
Settling time Ts(sec)	0.515sec	0.5600sec
Rise time Tr(sec)	0.3800sec	0.4150 sec
Steady state error ess%	0.0854%	1.5488e-004

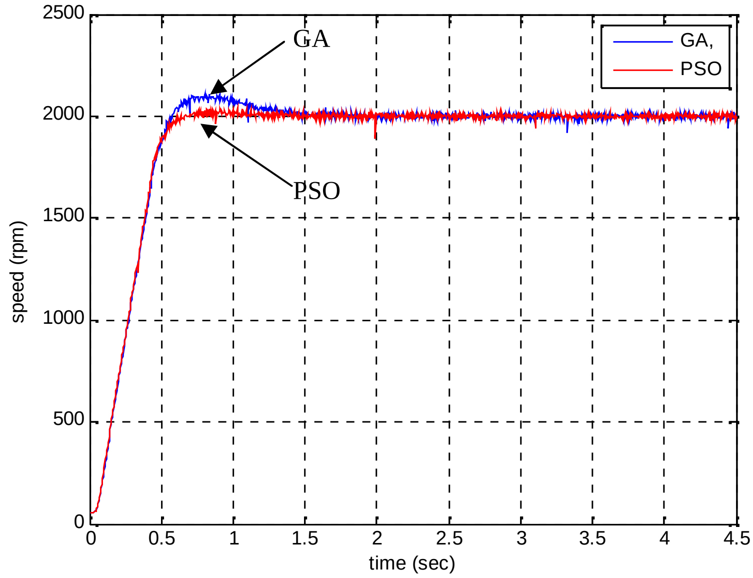

Figure 8: Experiment with respect to ITAE

Figures 9 and 10 illustrate the actual system and its identified model performance to maintain speed of multi-step set point with optimum PID controller tuned by GA and PSO respectively using (ITAE) fitness function.

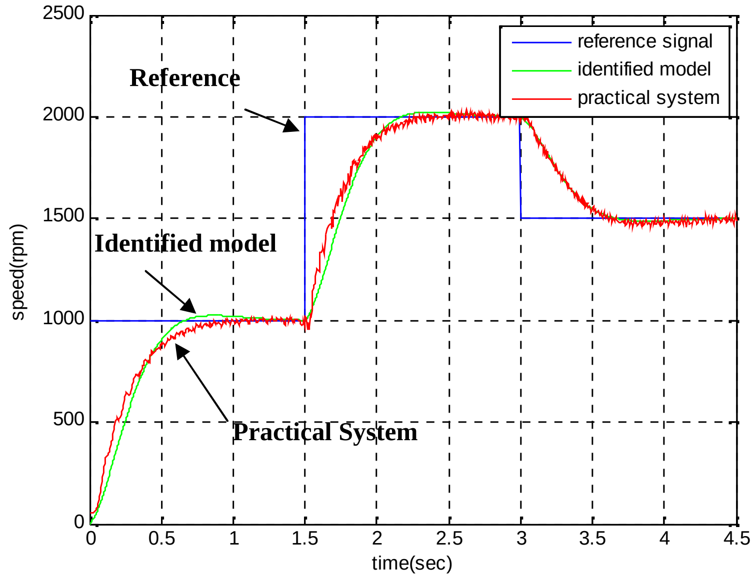

Figure 9: The speed response of multi-step speeds using GA-PID

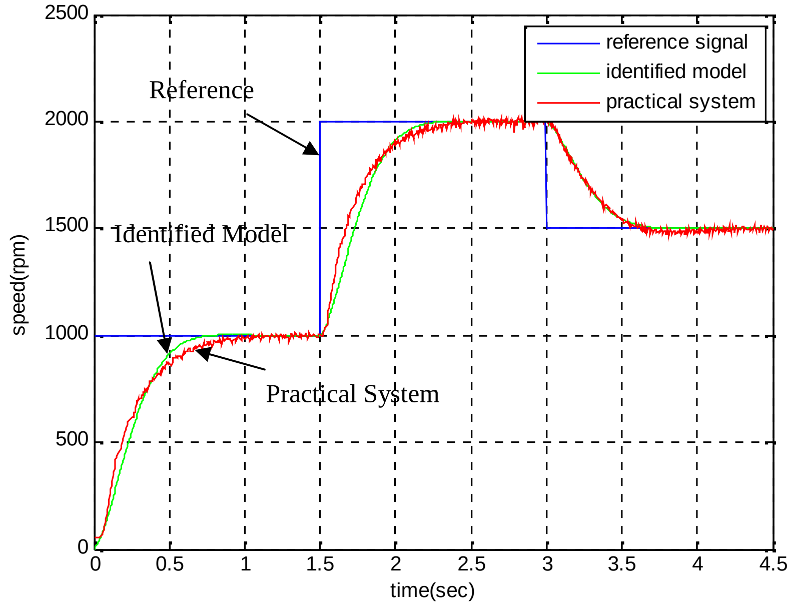

Figure 10: The speed response of multi-step speeds using PSO-PID

3.3. Motor Loading

Figure (11) shows the actual system speed response to maintain speed 2000 rpm with sudden load (1.2N.m) applied after 2 seconds with no feedback (open loop). It is clear that the speed decreases, and no recovery occurs. Figure (12) illustrates the actual system speed response with optimum PID controller tuned by GA and PSO techniques using ITAE fitness function. Clearly, the recovery time in case of PSO is smaller than that of GA.

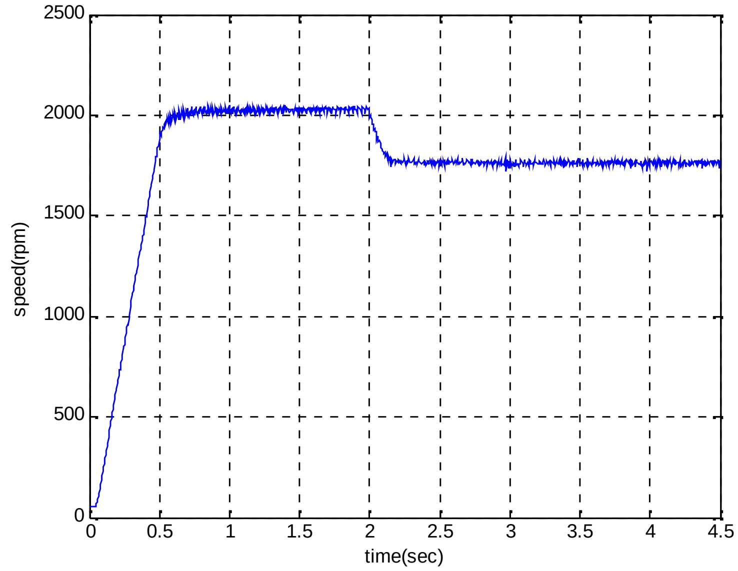

Figure 11: The speed response in open loop control

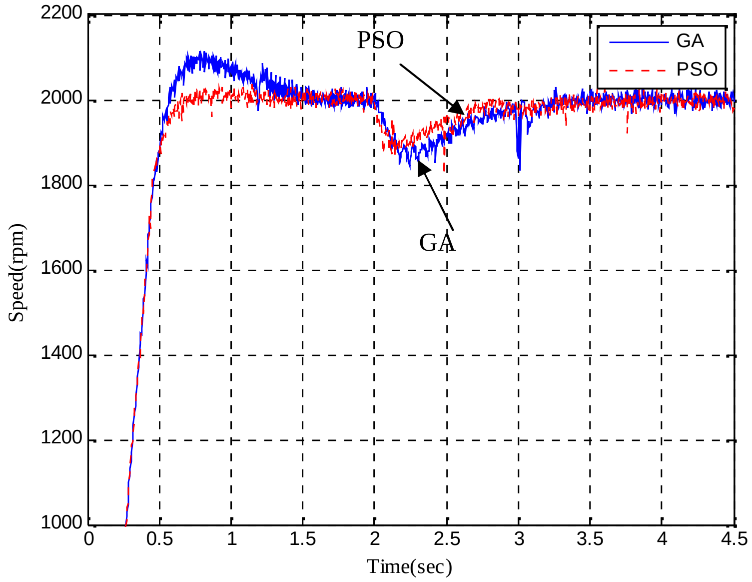

Figure 12: The speed response using (ITAE)

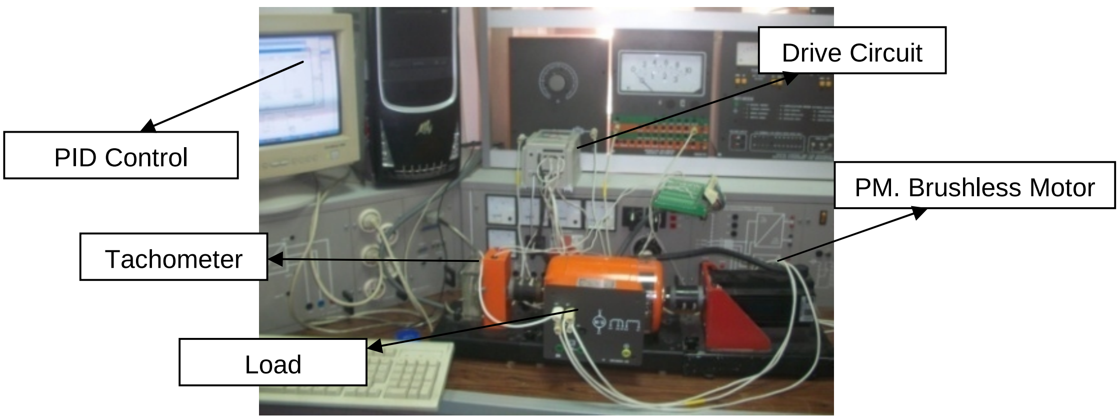

Figure 13: The experiment setup

4. CONCLUSIONS

The transfer function of the BLDC Motor and its Drive Circuit is derived using system identification technique. The optimization of BLDC Motor Drive controller parameters was derived thought GA and PSO algorithms. Simulation and experimental results proved that the PSO is more efficient than the genetic algorithm in seeking for the global optimum PID parameters with respect to the desired performance indices. Thus, the system performs better time response with the optimum PID controller. In addition, the PSO algorithm is easier to implement than the GA.

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