Results in Control and Optimization 19 (2025) 100549

Contents lists available at ScienceDirect

Results in Control and Optimization

journal homepage: www.elsevier.com/locate/rico

Parameter estimation and speed control of real DC motor with low resolution encoder

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ARTICLE INFO

Keywords:
Real brushed DC motor
Low resolution optical encoder
Parameter estimation
Particle swarm optimization
PI control

ABSTRACT

In this study, parameter estimation and speed control of a real brushed Direct Current (DC) motor are conducted. For parameter estimation, a popular iterative optimization algorithm, namely Particle Swarm Optimization (PSO), is used. The motor is assumed to have first-order dynamics, which are a reasonable assumption for most DC motors in practical use and two parameters representing the mathematical model of the model are estimated. The step response of the open-loop system is used as data for the parameter estimation algorithm. Using the estimated parameters simulations are conducted for closed loop Proportional-Integral (PI) control. Experiments on a real brushed DC motor are also conducted for closed-loop PI control of rotor speed. Speed of motor is measured using single channel low resolution optical encoder. Due to low resolution of speed sensor, precision of the whole system is limited and oscillations are observed in speed output measured. Controlling low-resolution sensor systems is important for two reasons. First, cost of the system is quite low compared with high resolution sensors. Second, for some real systems, especially with small physical dimensions, high resolution sensors may not be available at all. So, one of the important aspects of this study is to analyze low resolution sensor systems. As a closed loop controller, simple but popular PI controller is chosen to show the compatibility of experimental results with simulations. Oscillations around reference value are less than 10% in both simulations and experiment results. In real experiments, oscillations are slightly higher due to low resolution of encoder which is expected due to quantization error. Several parameters are used for controller and results are reported and discussed in corresponding sections.

1. Introduction

Brushed DC motors are one of the most versatile actuators used in many applications requiring speed and position control [1]. Speed control of brushed DC motors is important because high performance in speed control has a significant impact on the performance of systems that use it as a component like robots, CNC machines, automation systems and alike. Notable studies on brushed DC motor speed control include the following:

Komić and Dubravić [2] employed a microcontroller to record voltage/speed values from the DC motor and then transferred this data to the MATLAB/Simulink environment. They utilized the Parameter Estimation toolbox to determine the motor parameters and implemented a cascade control system comprising two tuned PI controllers.

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https://doi.org/10.1016/j.rico.2025.100549
Received 17 August 2024; Received in revised form 3 October 2024; Accepted 13 March 2025
Available online 16 March 2025

Jammousi et al. [3], employed the Ant Colony Optimization (ACO) algorithms to optimize the parameters of a sliding mode controller for a DC motor. Using MATLAB/Simulink, a DC motor model was developed and simulated with the addition of external uncertainties and disturbances. Simulation results demonstrate the effectiveness of the ACO tuning method in obtaining better performance from the DC motor in terms of speed control. The ACO-tuned sliding mode controller offers a more accurate response in the presence of parameter variations and external disturbances compared to manual tuning.

Rodríguez-Abreo et al. [4] proposed an approach for estimating dynamic DC motor models utilizing the meta-heuristic cuckoo search algorithm. This algorithm employs a cost function derived from current and speed error in the input voltage step, leading to enhanced accuracy in parameter estimation. A comparison was made between their modified algorithm, the original cuckoo search, and the Steiglitz-McBride [5] algorithm. The findings indicated that the modified version performed better in estimating parameters.

Hafez and Dhaouadi [6] highlight the importance of determining mechanical parameters like moment of inertia and viscous friction for accurate DC motor system modeling and control, as these details are often not provided by manufacturers. They applied modified Particle Swarm Optimization (PSO) techniques to estimate parameters in a model featuring a load connected to the motor shaft.

Niembro-Ceceña et al. [7] concentrate on parameter estimation and speed control, employing time series analysis to forecast back electromotive force (EMF) values for real-time adaptation of Proportional-Integral-Derivative (PID) controllers in both brushed and brushless DC motors. The authors suggest an Auto-Regression Moving Average (ARMA) model to estimate the evolving DC motor parameters influenced by system imperfections over time. Their approach involves updating the PID controller gains using the Simulink controller tuning toolbox.

Omar et al. [8] focused on the experimental implementation of model reference adaptive control (MRAC) for a DC motor without requiring parameter identification. The study aimed to develop a controller independent of system parameters to circumvent identification issues, thus saving time and ensuring robustness against online parametric variations. The experimental results showed that the motor successfully tracked the reference speed, with adaptation parameters converging towards their nominal values.

Vanchinathan and Selvaganesan [9] propose an Artificial Bee Colony (ABC) algorithm-tuned Fractional Order PID controller for a Brushless DC motor, aiming to improve performance across various speed and load conditions. They incorporate a kalman filter for speed estimation to address limitations of hall effect sensors. Simulation results show superior performance compared to genetic algorithm-tuned controllers.

Bouhentala et al. [10] combine fuzzy clustering estimation with sliding mode control for quadrotor systems with unknown elements and external disturbances. They introduce a novel Takagi-Sugeno interval-valued fuzzy model based on input-output data to estimate nonlinear unknown components. The control strategy adaptively estimates the system's model for use in sliding mode control.

Tuẩn et al. [11] presented a method for speed control of brushed DC motors using Finite Control Set-Model Predictive Control (FCS-MPC). This approach entails estimating motor parameters utilizing output speed response, as well as measured speed and armature current under load torque conditions. The efficacy of the proposed speed control algorithm is verified through experimentation, with results indicating that the FCS-MPC controller surpasses the performance of conventional PI controllers.

Nguyen et al. [12] compared three types of controllers - a standard PI controller, a fuzzy logic controller, and a fuzzy PI controller - using a real-time simulation system. The experimental results indicate that when motor parameters are accurately known, the PI controller delivers high performance. However, in scenarios involving complex models, the fuzzy PI controller demonstrates greater utility.

Zuo et al. [13] proposed two adaptive PI controllers for speed control of electric drives, utilizing model reference adaptive identification. These controllers are designed to automatically set PI controller gains in situations where mechanical parameters are unknown. Simulation results indicate that the adaptive PI controllers successfully identify mechanical parameters and surpass the classical PI controller in noise attenuation.

Hajari and Ray [14] presents a voltage-based current estimation technique for precise speed control of DC motor systems, which eliminates the need for high bandwidth current sensors and high-speed analog-to-digital converters (ADCs). The proposed current estimation technique is shown to improve accuracy while significantly reducing costs compared to high-bandwidth current sensors, adapt well to dynamically varying terminal voltage conditions, and exhibit superior performance in real-world scenarios.

Charkoutsis and Kara-Mohamed [15] proposed a Nonlinear PID (NLPID) controller tuned using Particle PSO for first order plus time delay systems, demonstrating improved performance and robustness compared to conventional controllers.

Manuel et al. [16] compared five metaheuristic algorithms for optimizing PID controllers in DC motor speed control, finding that all algorithms achieved similar optimal gains given sufficient runs, with Teaching Learning Based Optimization (TLBO) being the fastest. They also noted that a Fuzzy Logic Controller (FLC) outperformed the metaheuristic-based PIDs.

Sachan and Swarnkar [17] investigated four metaheuristic algorithms for mobile robot speed regulation, concluding that Grey Wolf Optimization (GWO) control was superior to conventional control for time-varying and nonlinear mobile robot systems in terms of time response parameters and accuracy. Similar works can be found in Refs. [18–25], where these studies highlight the potential of metaheuristic algorithms and intelligent control strategies for improving system performance across various applications.

In this study a real brushed DC motor with low resolution optical encoder is used for parameter estimation and closed loop speed control framework. . The novelties of this paper are parameter estimation of a real brushed DC motor with PSO algorithm and PI control of a real brushed DC motor with various PI parameters all done with low resolution optical encoder. Using low resolution encoder presents some problems but has main advantages of low cost and easy production especially for very small systems. Note that the combination of PSO based parameter estimation and PI control on real brushed DC motor is itself a novel combination with the added novelty of using low resolution encoder which may be mandatory for very small systems like nanorobots. Parameter estimation is done using Particle Swarm Optimization (PSO) technique on the step response of motor. Closed loop control simulations are conducted with estimated parameters of motor. Experiments are conducted on real DC Motor with different controller parameters.

2. Material and methods

2.1. Mathematical model of brushed DC motor

A brushed DC motor with gearbox and optical encoder is used in this study for experimental work. Electromechanical diagram and mathematical model of DC motor are given below Fig. 1.

V_a is input armature voltage, i_a is armature current, R_a is armature resistance, L_a is armature inductance, e_b is back-emf voltage, T_m is motor torque, w is rotor angular speed in rad/s, J is rotor inertia, b is viscous friction due to rollers and T_l is load torque.

Using Kirchhoff's Laws electrical system's mathematical equation is:

$$V_a = R_a i_a + L_a \frac{di_a}{dt} + e_b \tag{1}$$

Back-emf is proportional to rotor velocity:

$$e_b = K_b \dot{\theta} \tag{2}$$

Motor torque is proportional to armature current:

$$T_m = K_m i_a \tag{3}$$

Finally, using Newton's second law of motion modified for rotational systems mechanical system's mathematical equation is:

$$T_m - T_l = J\ddot{\theta} + b\dot{\theta} \tag{4}$$

By solving the aforementioned equations, a second-order system is derived, depicting the relationship between the armature voltage input and the rotor speed output [26]. Below is the transfer function obtained using the Laplace Transform for the second order system:

$$\frac{\Omega(s)}{V_a(s)} = \frac{K_m}{L_a J s^2 + (R_a J + b L_a)s + (K_m K_b + R_a b)} \tag{6}$$

In most practical brushed DC motors, the armature inductance (L_a) is significantly smaller than the armature resistance (R_a). This leads to the system being approximated as a first-order system. The transfer function of such a system can be represented as follows:

$$\frac{\Omega(s)}{V_a(s)} = \frac{1}{coefficient0 + coefficient1 * s} \tag{7}$$

In order to simulate any brushed DC motor of practical use with the first order system assumption above, two parameters, namely coefficient0 and coefficient1 must be estimated. Controllability and stability properties of Hilfer fractional equations, estimation of running time parameters of equations in DC motor control systems and contribution of the system to stable operation can be found in [27].

Note that effective armature input voltage is given using an H-bridge with pulse-width-modulation input signal and angular speed output is measured using a single-channel optical encoder which is explained below.

2.2. Optical encoder for speed measurement

For speed measurement, a single-channel optical encoder with low resolution of 96 pulse-per-revolution is used. Working principle of optical encoder is based on optoelectronics as shown in Fig. 2 below.

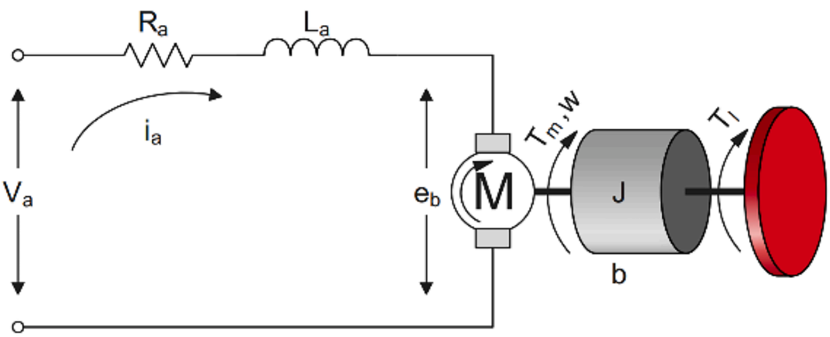


Fig. 1. Electromechanical diagram of DC motor.

An infrared (IR) LED transmitter emits invisible light, which is detected by an IR phototransistor receiver. LED and phototransistor are separated by a circular wheel with holes which is attached to motor shaft. As the wheel rotates, holes are passing between LED and phototransistor with speed proportional to the motor velocity. When a hole is positioned between the LED and the phototransistor, light illuminates the phototransistor, leading to a change in the output voltage to $V_{cc} = 3.3$ Volts; otherwise, the output voltage remains at 0 Volts. Continuous rotation of the wheel causes a square wave output frequency of which is proportional to the motor speed. By measuring this frequency, motor speed is measured.

There are two methods for estimating speed of motor. If the encoder is high resolution and desired speed is relatively high, counting the number of pulses per millisecond will give speed estimation. The second method which is used in this study is for low resolution encoders which is based on measuring the period of each pulse using a timer inside digital computing unit.

2.3. Particle swarm optimization for parameter estimation

Particle Swarm Optimization (PSO) is used to estimate the parameters of the DC motor from step response curve. PSO is an iterative optimization algorithm used to solve optimization problems that are difficult or impossible to solve by analytical methods [28]. PSO is based on a number of particles, called swarm, each represent a hypothesis for parameters to be estimated. In each iteration a cost or profit of each particle is computed first, then new position of each particle is computed according to the cost or profit scores of particles. In order to compute new position of each particle, a velocity for that particle is computed using three independent components. The velocity of each particle depends on three factors: first, the previous velocity of the particle; second, the particle's known best position up to that iteration; and third, the global best position of all particles up to that iteration. These three components are used to estimate new velocity of the particle which is used to update the next position of the particle. Fig. 3 shows the flow chart of particle swarm optimization.

2.4. Proportional integral closed loop controller

After the estimation of motor parameters with PSO algorithm, simulations and experiments on real DC motor are conducted for closed loop Proportional-Integral (PI) control of speed of DC motor. PI control is one of the simplest but most successful closed loop control algorithms especially for simple linear systems. Only two parameters are needed to compute the control output, namely Kp and Ki, proportional and integral constants.

Fig. 4 shows the flow chart of the PID Control algorithm.

3. Results

In the context of parameter estimation, a step input of 10 Volts was applied, and the angular speed was measured over a duration of 1 second. Below is a plot illustrating the step response of the DC motor in this study.

Note that the oscillations in speed are mainly due to low-resolution encoder. This data is the one we used for parameter estimation using PSO algorithm. Below is the plot of estimation output after 200 epochs.

With estimated parameters of DC motor, which are coefficient0 and coefficient1 of first order transfer function, PI control simulations are conducted for various K_p and K_i parameters of PI controller. Below are the results for four different controller parameter configurations in Fig. 7. Red line is reference motor speed while blue line is real output motor speed. Simulations are run for 1 second, which is shown in the horizontal axis. Note that for K_p=10, oscillation amplitudes are smaller than K_p=100. As K_p increases, the system

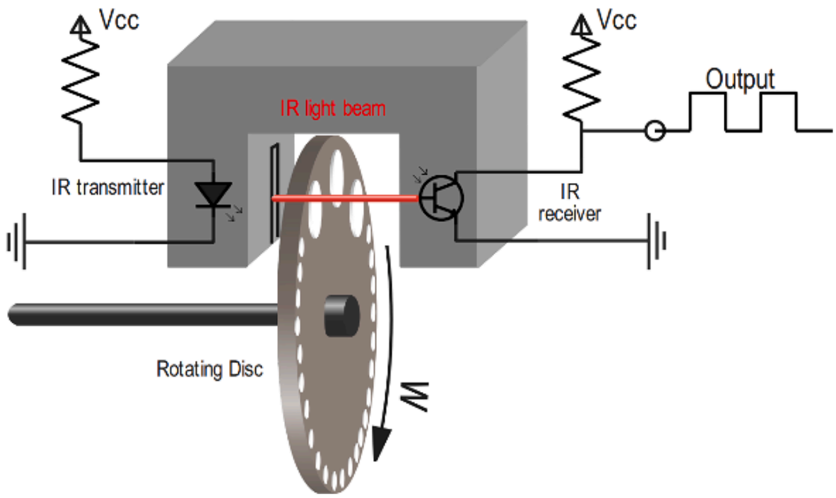


Fig. 2. Working principle of optical encoder.

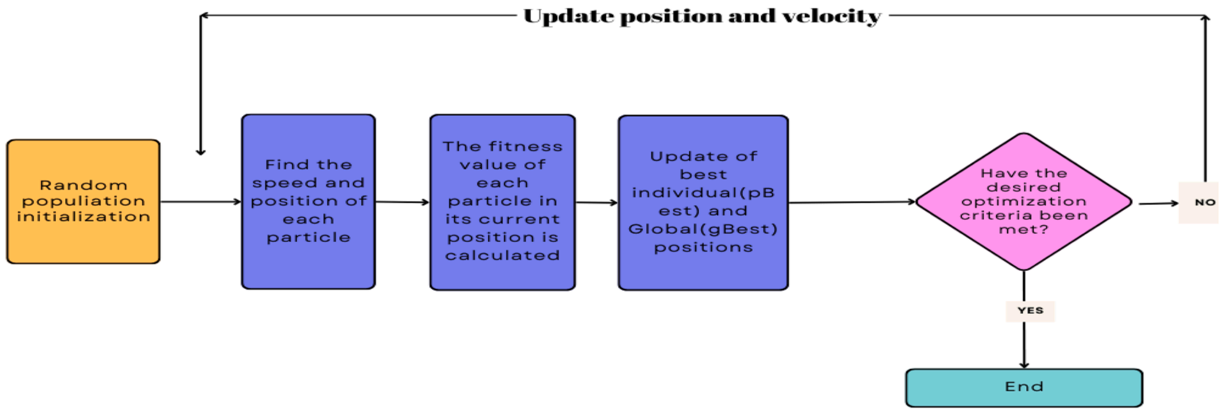


Fig. 3. Flowchart of PSO algorithm.

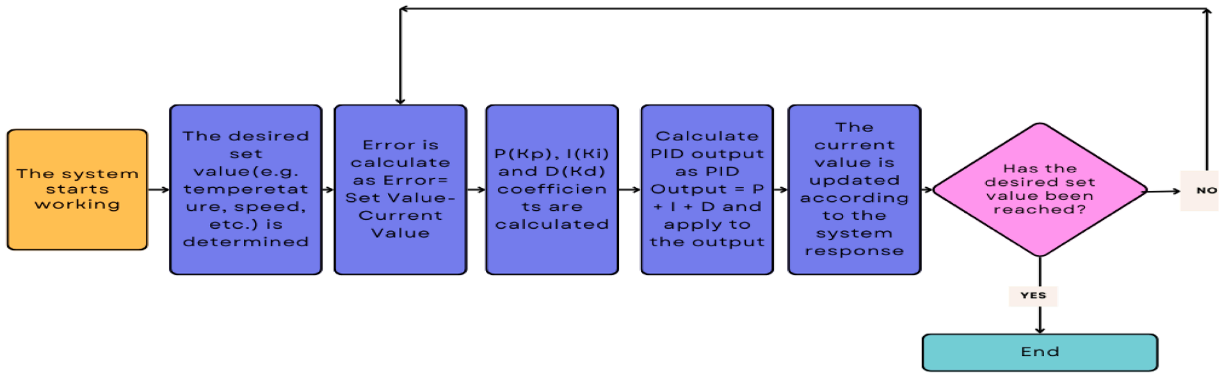


Fig. 4. Flowchart of PID Controller.

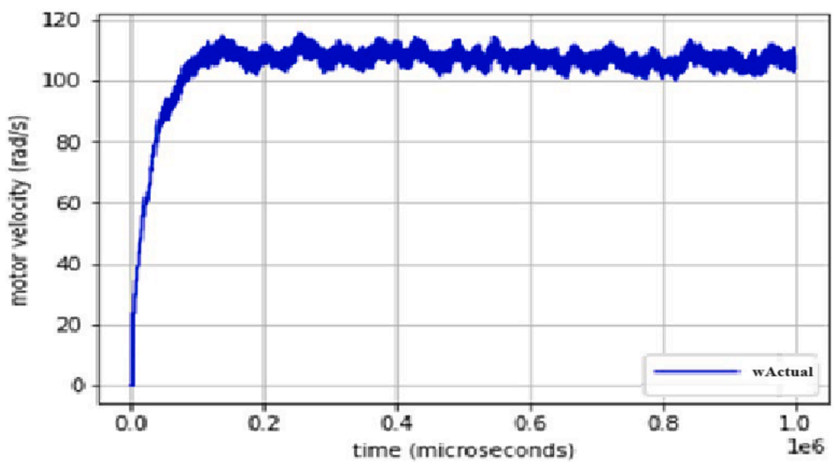


Fig. 5. Step response of DC motor to 10 Volt step armature voltage input.

becomes less stable, which is expected.

Below are the experiment results of real DC motor PI control for various controller parameters Fig. 8.

Note that results shown in the figures above are absolute values for the motor used. In order to normalize the results, a separate experiment is conducted to find the maximum velocity of the motor. Maximum armature voltage of the motor is 12 Volts, so this maximum 12 Volts is applied to the motor and velocity is measured. The measured maximum velocity of the motor is 174.097 rad/sec under 12 Volts armature voltage. This maximum velocity is used to normalize the results and below are shown in Fig. 9 the normalized

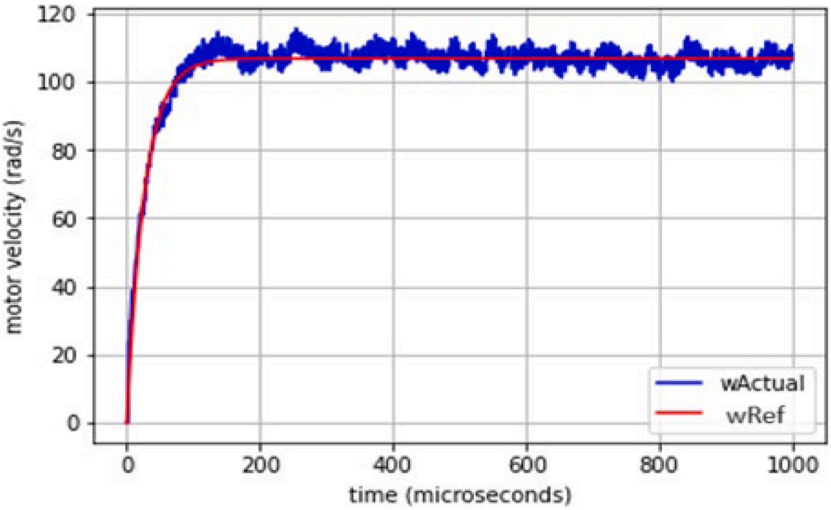


Fig. 6. Measured speed with blue, simulated speed with estimated parameters with red.

results for real DC motor PI control.

4. Discussion

Simulation results are compatible with experiment results. Note that for a simple first order linear platform like in our setup, analytic parameter estimation is also possible which may be easier than estimation with PSO. So, one may question usage of PSO algorithm for parameter estimation at all. Although analytic methods may work well for parameter estimation of simple linear systems, they become intractable when the system gets more complicated. For nonlinear systems of higher dimension with a greater number of inputs and outputs, like mobile robots [29] or quadcopters [30], mathematical models become much more complicated and impossible to solve analytically. In these types of complicated systems, iterative optimization algorithms like PSO are expected to work well, may be with extra acceptable amount of computation time and memory.

It is also seen that simulation results and experimental results deviate notably for small controller constants of K_p=10 and K_i=1 configuration as seen in Figs. 5a and 6a. This is due to static friction in the gearbox and bearings of the DC motor, which manifests for low controller constants. Note that this static friction is very hard to model and is not included in the simulations. Simple PI controller seems to give acceptable performance results for simple linear system used in this study. As the plant dynamics becomes more complicated, more advanced controller structures will be needed to deal with complex input-output relationship of system under control.

Only single-input single-output brushed DC motor which is a linear system is studied in this paper which is a limitation of this study. Nonlinear systems with multi-input multi-output scheme can assert certain problems but are expected to show acceptable results with more computation time to calculate the optimal parameters.

5. Conclusion and future work

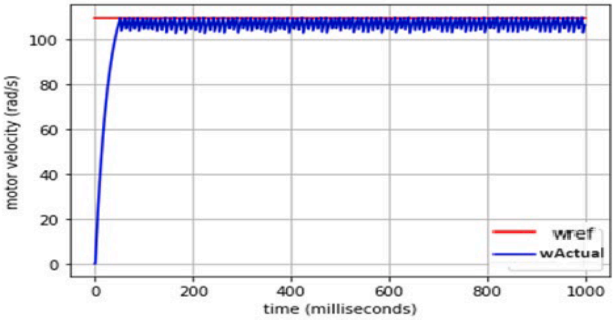
Parameter estimation and closed loop speed control of brushed DC motor is done in this study. Speed of DC motor is measured using single channel low resolution optical encoder. Motor is assumed to be a first order system with two parameters and parameters are estimated from step response curve using PSO algorithm. Both simulations and experiments on real brushed DC motor is conducted using closed loop PI control with several parameters. Encouraging results are obtained and reported. As future work more complex systems with higher order nonlinear dynamics are planned to be studied such as mobile robots and quadcopters.

Declaration of competing interest

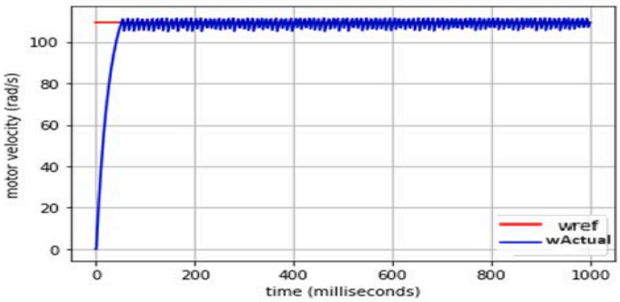
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.



(a)



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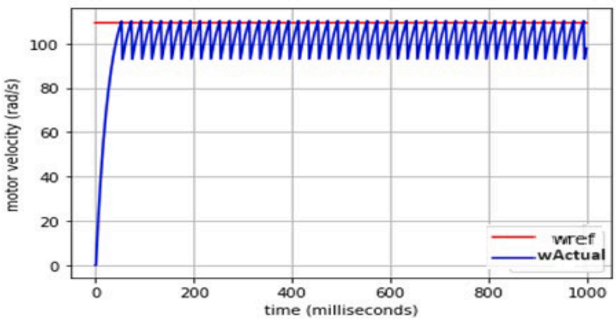

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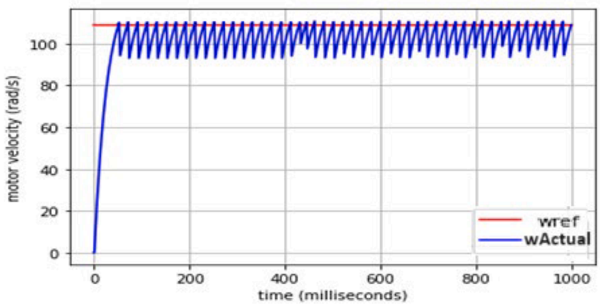
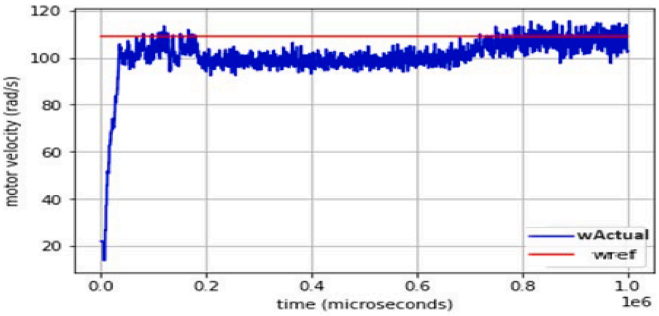
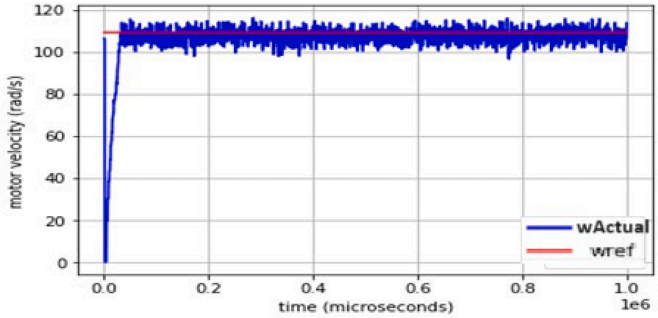


(d)

Fig. 7. Simulation of PI controller with [Kp,Ki] (a) [10,1] (b) [10,10] (c) [100,1] (d) [100,10].



(a)



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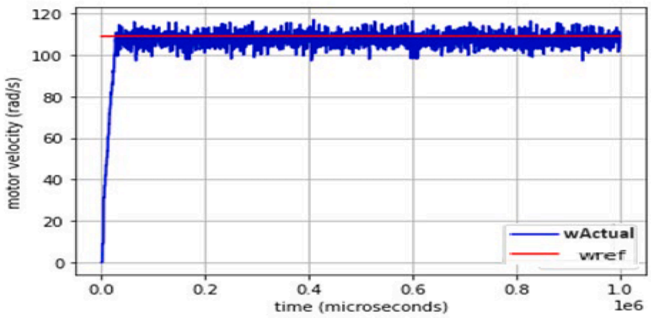

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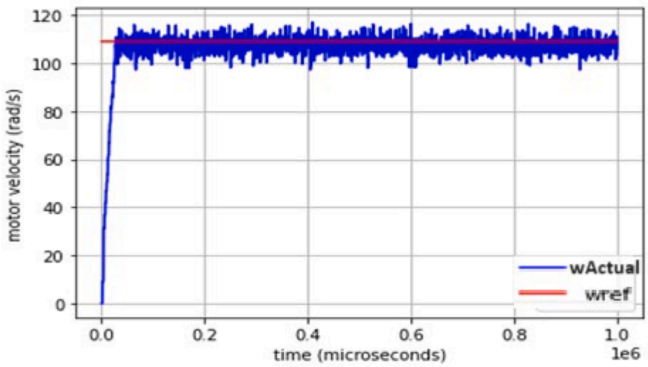

(d)

Fig. 8. Experiment results of PI controller with [Kp,Ki] (a) [10,1] (b) [10,10] (c) [100,1] (d) [100,10].

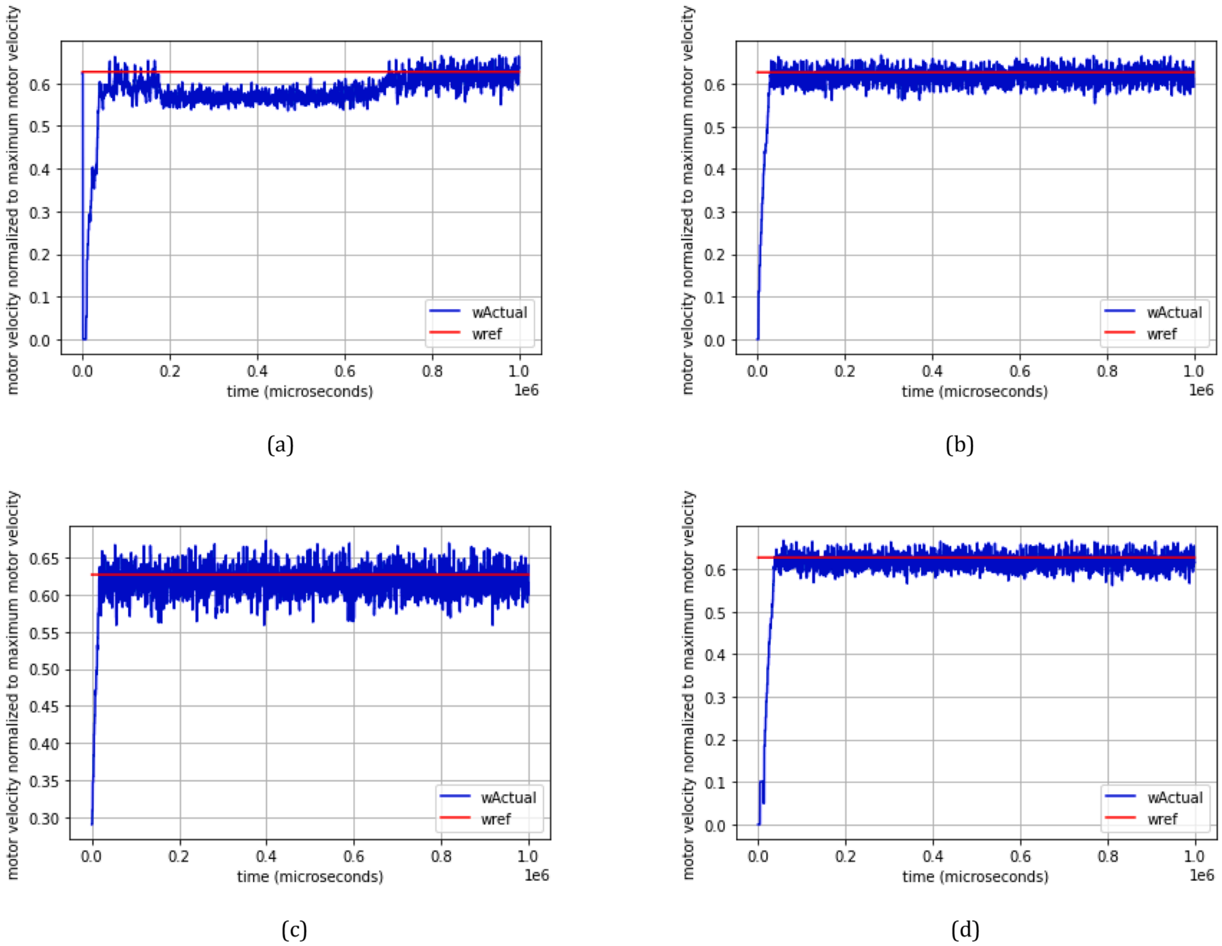

Fig. 9. Normalized experiment results of PI controller with [Kp,Ki] (a) [10,1] (b) [10,10] (c) [100,1] (d) [100,10].

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