A Data-Driven Sigmoid-based PI Controller for Buck-Converter Powered DC Motor

M.A. Ahmad, R.M.T. Raja Ismail
Instrumentation and Control Engineering Research Group
Faculty of Electrical & Electronics Engineering
Universiti Malaysia Pahang
26600 Pekan, Pahang, Malaysia
Email: mashraf@ump.edu.my

***Abstract*—This paper presents a novel data-driven sigmoid-based PI for tracking of angular velocity of dc motor powered by a dc/dc buck converter. A global simultaneous perturbation stochastic approximation (GSPSA) is employed to find the optimum sigmoid-based PI parameters such that the angular velocity error is minimized. The merit of the proposed approach is that it can produce fast PI parameter tuning without using any plant model by measuring the I/O data of the system. Moreover, the proposed PI parameters that are varied based on sigmoid function of angular velocity error has great potential in improving the control performance compared to the conventional PI controller. A well-known buck converter powered DC motor model is considered to validate our data-driven design. In addition, the performances of the proposed method are examined in terms of angular velocity trajectory tracking and duty cycle in comparison with other existing approaches. Numerical example shows that the data-driven sigmoid-based PI approach provides better control performances as compared to existing methods.**

***Index Terms*—Data-driven, variable structure PI, buck converter powered dc motor, tracking control.**

I. Introduction

Nowadays, many applications of dc motors require a high precision motion, such as rolling mills, electric cranes, conveyor belts and liquid carriers. Generally, many researchers apply conventional pulse width modulation (PWM) signals to drive the dc motor. However, this approach provides an unsatisfactory dynamic behavior due to hard switching strategy, which causing sudden changes in the current and voltage of the dc motor [1]. In order to solve this issue, a dc/dc buck converter is utilized, which allows to control the stepless velocity and smoothness. In particular, it can track both desired angular velocity and position trajectory by adjusting the required motor input voltage.

So far, a large number of methods have been widely reported in controlling buck-converter powered dc motor. In [2], a classical proportional-integral (PI) controller is utilized to regulate the the dc motor angular velocity. Here, they apply the controller to a fourth-order mathematical model of buck converters with a dc motor. Likewise, for the same mathematical model, a feedback controller based on damping injection and energy shaping has been synthesized in [3]. In [1], [4] and [5], a flatness based approach is employed for a smooth tracking of angular velocity of dc motor driven by dc/dc buck converter. The controller in [1] and [4] was obtained through a fourth-order model deduced in [2], while the controller in [5] was designed based on simplified second-order model. Note that in the second-order model, it is assumed that the converter capacitor current and the motor armature inductance to be negligible. Furthermore, a GPI control based on sliding mode-delta modulation is proposed in [6]. Here, they used the simplified mathematical model in [5]. Moreover, in [7], a backstepping controller with both adaptive and non-adaptive versions were derived from fourth-order mathematical model. Their numerical simulation show that the adaptive version provides better performance with load torque variations. Other control approaches for dc/dc buck converter powered dc motors include PI and LQR controllers [8], PI-Fuzzy controller [9], neural network controller [10], H_∞ controller [11], robust control law based on active disturbance rejection [12], and two-stage control based on differential flatness [13].

As shown in the above, most of the designed approaches has focused on the model-based controllers, which are derived from second or fourth-order mathematical model. However, it is difficult to apply the traditional model-based controller in real buck-converter powered dc motor systems due to several reasons, such as, the inaccuracy of simplified model, unmodeled dynamic problems, and huge gap between control theory and real applications. As a results, a data-driven controller will be more convincing solution. In particular, the data-driven controller is designed based on input-output data of the systems without using explicit or implicit information of the plants. Here, the data-driven controller based on PID structure is highly preferable due to its simplicity in design and implementation [14]. Furthermore, the performance of conventional PID controller can be improved by modifying it to variable structure PID (VS-PID), which has been widely reported in many literatures [15]–[17]. Hence, it is worth evaluating the capability of data-driven VS-PID controller for tracking of angular velocity trajectory of buck-converter powered dc motor.

This paper aims to explore the capability of the data-driven sigmoid-based PI for tracking of angular velocity trajectory of buck-converter powered dc motor. Note that, the sigmoid-based PI, which is in the family of VS-PID, has been introduced in [17]. It offers great potential to improve the control performance by varying the PI parameters based on angular velocity error. However, the work in [17] does not contains a clear explanation of data-driven controller tuning. Here, a global simultaneous perturbation stochastic approximation (GSPSA) [18] is utilized to find the sigmoid-based PI parameters such that the angular velocity error is minimized. Furthermore, the GSPSA algorithm was known to be a promising tool for controller tuning problems. This is because this algorithm, which is mainly derived from the conventional SPSA method [19], is capable to solve variety of optimization problems with less number of evaluated objective functions even for high-dimensional parameter tuning [20]–[22]. In particular, it has been shown that the GSPSA algorithm can achieve better local optimal values compared to the standard SPSA in PID tuning of MIMO systems [14]. Our data-driven controlled design is then validated using a well-known buck-converter powered dc motor model in [2]. Next, the performances of the proposed controller are analyzed in terms of angular velocity trajectory tracking and duty cycle input energy. Here, the convergence speed is recorded based on the number of evaluated objective functions. Finally, a comparative assessment between the proposed data-driven sigmoid-based PI and conventional PI [8] and PI-Fuzzy [9] is presented.

The organization of this paper is presented as follows. In Section II, the problem of data-driven sigmoid-based PI in minimizing the angular velocity trajectory tracking error of buck-converter powered dc motor is formulated. In Section III, the methodology of GSPSA-based algorithm, which is used for sigmoid-based PI tuning, is summarized. The proposed controller is then validated to a given buck-converter powered dc motor model in Section IV. The analysis and performances comparison between the proposed controller and other existing control methods are also demonstrated. Finally, the summary of this paper is presented in Section V.

Notation: The symbol $\mathbb{R}$ represents the real numbers set and the symbol $\mathbb{R}_+$ represents the positive real numbers set. Let V be the random variable. Then, the probability of event $V = E$ is given by $\mathbb{P}(V = E)$. For $\gamma \in \mathbb{R}_+$, $\text{sat}_\gamma : \mathbb{R}^n \to \mathbb{R}^n$ is the saturation function whose ith element is represented as follows:

$$\text{Each element of } \underset{\gamma}{\text{sat}}(\boldsymbol{x}) = \begin{cases} \gamma & \text{if } \gamma < x_i, \\ x_i & \text{if } -\gamma \leq x_i \leq \gamma, \\ \gamma & \text{if } \gamma < x_i, \end{cases}$$

where $x_i \in \mathbb{R}$ is the ith element of $\boldsymbol{x} \in \mathbb{R}^n$.

II. Problem Statement

Consider the sigmoid-based PI controller of buck-converter powered dc motor system in Figure 1 where $r(t)$ is the reference, $u(t)$ is the control input, $y(t)$ is the angular velocity and $e(t)$ is error between the reference and the angular velocity. The buck-converter powered dc motor is denoted as a plant G. The sigmoid-based PI controller is given by

$$K_{PI}(s) = \tilde{K}_P + \frac{\tilde{K}_I}{s} \tag{1}$$

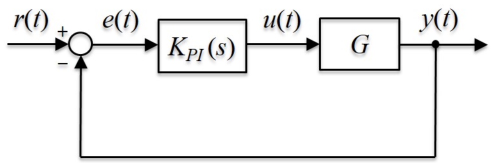

Fig. 1. Sigmoid-based PI control system

where

$$\tilde{K}_P = K_{P\,\min} + \frac{|K_{P\,\max} - K_{P\,\min}|}{1 + \mathrm{e}^{-\alpha_P(e(t) - \beta_P)}} \tag{2}$$

and

$$\tilde{K}_I = K_{I\,\min} + \frac{|K_{I\,\max} - K_{I\,\min}|}{1 + \mathrm{e}^{-\alpha_I(e(t) - \beta_I)}}. \tag{3}$$

In (2) and (3), $K_{P\,\min} \in \mathbb{R}$ and $K_{P\,\max} \in \mathbb{R}$ are lower and upper bounds of $\tilde{K}_P$, respectively, $K_{I\,\min} \in \mathbb{R}$ and $K_{I\,\max} \in \mathbb{R}$ are lower and upper bounds of $\tilde{K}_I$, respectively, $\alpha_P \in \mathbb{R}$ and $\alpha_I \in \mathbb{R}$ are coefficients to adjust the curve sharpness between lower and upper bounds of $\tilde{K}_P$ and $\tilde{K}_I$, respectively, and $\beta_P \in \mathbb{R}$ and $\beta_I \in \mathbb{R}$ are coefficients to shift the center of curve between lower and upper bounds of $\tilde{K}_P$ and $\tilde{K}_I$, respectively. For simplicity of design parameter tuning, we define $\Delta_P = |K_{P\,\max} - K_{P\,\min}|$ and $\Delta_I = |K_{I\,\max} - K_{I\,\min}|$. Note that the values of $\tilde{K}_P$ and $\tilde{K}_I$ are now varied according to $e(t)$ signal, instead of using fix proportional and integral gains in conventional PI controller. Please see [17] for the detail structure of sigmoid-based PI controller.

Remark 2.1. Our proposed sigmoid-based PI is different from [17] in several ways. Firstly, we consider a unique value of curve sharpness coefficient (i.e., α_P and α_I) for each $\tilde{K}_P$ and $\tilde{K}_I$. Secondly, we also introduce a new coefficient (i.e., β_P and β_I) to allow the shifting of the curve center. Both modifications are expected to provide more flexibility and variation to our sigmoid-based PI controller. Finally, we don't give any restriction to error signal $e(t)$ in (2) and (3), such as $|e(t)|$ (as proposed by [17]), to avoid any limitation to the sigmoid function.

Let the design parameter is denoted by $\boldsymbol{\theta} = (K_{P\,\min}, \Delta_P, K_{I\,\min}, \Delta_I, \alpha_P, \alpha_I, \beta_P, \beta_I)^T \in \mathbb{R}^8$. Then, the performance of the control system in Figure 1 is evaluated based on the objective function

$$J(\boldsymbol{\theta}) = w_1 \int_{t_0}^{t_f} e(t)^2 dt + w_2 \int_{t_0}^{t_f} u(t)^2 dt, \tag{4}$$

where w_1 and w_2 are weighting factors that are decided by the designer. Here, the first term and the second term in the right hand-side of (4) corresponds to the tracking error and control input, respectively. Moreover, the interval $[t_0, t_f]$ represents the duration of control performance assessment, where $t_0 \in 0 \cup \mathbb{R}_+$ and $t_f \in \mathbb{R}_+$. Then, the data-driven sigmoid-based PI for angular velocity tracking problem is given as follows:

Problem 2.1. The buck-converter powered dc motor control system in Figure 1 is given. Then, find a sigmoid-based PI controller $K_{PI}(s)$, which minimizes $J(\boldsymbol{\theta})$ with respect to $\boldsymbol{\theta}$ by using the input data $u(t)$ and output data $y(t)$.

III. Design of Sigmoid-based PI Controller using GSPSA

This section explains the key method to the solution of Problem 2.1. First, we briefly explain the GSPSA algorithm [18]. Then, we show the implementation of the data-driven sigmoid-based PI controller design based on the GSPSA algorithm for minimizing the error of angular velocity trajectory tracking for buck-converter powered dc motor.

A. Review on GSPSA

GSPSA is a stochastic approximation algorithm that find the design parameters such that a pre-specified objective function is minimized. We define a general optimization problem by

$$\min_{z\in\mathbb{R}^n} h(\boldsymbol{z}), \tag{5}$$

where $z \in \mathbb{R}^n$ is the design parameter and $h : \mathbb{R}^n \to \mathbb{R}$ is the objective function.

In the GSPSA algorithm [18], the design parameter is iteratively updated to find a local optimal solution $z^* \in \mathbb{R}^n$ of (5). The updated equation is expressed by

$$\boldsymbol{z}(k+1) = \boldsymbol{z}(k) - \hat{a}(k)\boldsymbol{v}(\boldsymbol{z}(k), \boldsymbol{r}_1(k)) + \hat{b}(k)\boldsymbol{r}_2(k) \tag{6}$$

for $k = 0, 1, \ldots$, where $\boldsymbol{v}(\boldsymbol{z}(k)$ is the approximation of the gradient between two perturbations, which is defined as

$$\begin{aligned}&\boldsymbol{v}(\boldsymbol{z}(k), \boldsymbol{r}_1(k))\\ &= \begin{bmatrix} \dfrac{h(\boldsymbol{z}(k)+\hat{c}(k)\boldsymbol{r}_1(k)) - h(\boldsymbol{z}(k)-\hat{c}(k)\boldsymbol{r}_1(k))}{2\hat{c}(k)r_{11}(k)} \\ \vdots \\ \dfrac{h(\boldsymbol{z}(k)+\hat{c}(k)\boldsymbol{r}_1(k)) - h(\boldsymbol{z}(k)-\hat{c}(k)\boldsymbol{r}_1(k))}{2\hat{c}(k)r_{1n}(k)} \end{bmatrix},\end{aligned} \tag{7}$$

$\hat{a}(k)$ and $\hat{b}(k)$ are the gain, $\boldsymbol{r}_1(k) \in \mathbb{R}^n$ and $\boldsymbol{r}_2(k) \in \mathbb{R}^n$ are random vectors that are produced independently. In (7), $\hat{c}(k)$ is another gain and $r_{1i}(k)$ is the ith element of a random vector $\boldsymbol{r}_1(k) \in \mathbb{R}^n$. The detail of the GSPSA algorithm and also the information to select $\hat{a}(k)$, $\hat{b}(k)$, $\hat{c}(k)$ and the random vectors, $\boldsymbol{r}_1(k)$ and $\boldsymbol{r}_2(k)$ is reported in [18] and [19]. In the algorithm, an example of termination criterion is based on the maximum number of iterations, i.e., the algorithm terminates after a user-determined number of iteration $k_{\max}$. Then, the algorithm terminates with the solution $\boldsymbol{z}^* := \arg \min_{\boldsymbol{z}\in\{\boldsymbol{z}(0),\boldsymbol{z}(1),\ldots,\boldsymbol{z}(k+1)\}} h(\boldsymbol{z})$.

B. Data-driven sigmoid-based PI design

The GSPSA algorithm in the previous section (Section III-A) is adopted for data-driven sigmoid-based PI tuning. In order to obtain a fast design parameter searching, a logarithmic scale is employed to each element of $\boldsymbol{\theta}$ by setting $[\theta_1\ \theta_2 \cdots\ \theta_8]^T := [10^{z_1}\ 10^{z_2}\ \cdots\ 10^{z_8}]^T$ with $J([10^{z_1}\ 10^{z_2}\ \cdots\ 10^{z_8}]^T)$. Finally, the data-driven design procedure is explained in the following steps:

Step 1: Set the maximum iteration numbers $k_{\max}$ and $z_i = \log\theta_i$ for $i = 1, 2, \ldots, 8$. Then, set the initial design parameter $\boldsymbol{z}(0)$.
Step 2: Compute the GSPSA algorithm in (6) based on the objective function in (4).
Step 3: After $k_{\max}$ iterations, the optimal design parameter $\boldsymbol{z}^* := \boldsymbol{z}(k_{\max}) \in \mathbb{R}^8$ is obtained. Then, $\boldsymbol{\theta}^* := ([10^{z_1^*}\ 10^{z_2^*}\ \cdots\ 10^{z_8^*}]^T)$ is adopted to the sigmoid-based PI controller $K_{PI}(s)$ in Figure 1.

Remark 3.1. In the conventional GSPSA algorithm in (6), it is not guarantee that the algorithm consistently yields a stable convergence during the iterative tuning. This is because there is a case that the design parameters may become very huge and subsequently produces unstable condition. Therefore, we adopt a modified GSPSA algorithm to avoid this problem, which has been proposed in [23]. In particular, a saturation function $\mathrm{sat}_\gamma(\cdot)$ has been used in (6). That is,

$$\boldsymbol{z}(k+1) = \boldsymbol{z}(k) - \underset{\gamma}{\mathrm{sat}}(\hat{a}(k)\boldsymbol{v}(\boldsymbol{z}(k), \boldsymbol{r}_1(k)) + \hat{b}(k)\boldsymbol{r}_2(k)). \tag{8}$$

In this study, we use the modified updated law in (8) instead of (6).

IV. Numerical Example

The performance investigation of the data-driven sigmoid-based PI controller based on GSPSA is presented in this section. We firstly describe the model of buck-converter powered dc motor in [2]. Then, the GSPSA based algorithm is implemented to the given model.

A. Buck-converter powered dc motor model

An electro-mechanical circuit of buck-converter powered dc motor system is shown in Figure 2. The switching mechanism is indicated by the multiplication of input voltage U_e with the duty ratio $\delta \in [0, 1]$. The ohmic resistance of coil windings in the model is denoted by R_L. The dc motor parameters are represented by an inductance L_M, ohmic resistance R_M, and electromagnetic source ωK_E where ω is angular velocity. Other parameters of the system are inductor L and capacitor C. For the input $u(t) := \delta$ and the output $y(t) := \omega$, the complete model of buck-converter powered dc motor system [2] is given by

$$G = \left[\begin{array}{c|c} \boldsymbol{A} & \boldsymbol{B} \\ \hline \boldsymbol{C} & \boldsymbol{D} \end{array}\right], \tag{9}$$

where

$$\boldsymbol{A} = \begin{bmatrix} -\frac{R_L}{L} & -\frac{1}{L} & 0 & 0 \\ \frac{1}{C} & 0 & -\frac{1}{C} & 0 \\ 0 & \frac{1}{L_M} & -\frac{R_M}{L_M} & -\frac{K_E}{L_M} \\ 0 & 0 & \frac{K_M}{J_M} & 0 \end{bmatrix}, \quad \boldsymbol{B} = \begin{bmatrix} \frac{U_e}{L} \\ 0 \\ 0 \\ 0 \end{bmatrix},$$

$$\boldsymbol{C} = \begin{bmatrix} 0 & 0 & 0 & 1 \end{bmatrix}, \quad \boldsymbol{D} = 0.$$

In (9), J_M and K_M are defined as moment of inertia and tachogenerator of the motor, respectively. Furthermore, the amplifier resistances R_4 and R_6 are neglected in the model since their values are very small.

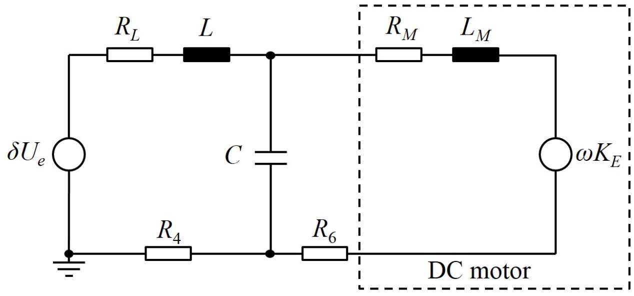

Fig. 2. Buck-converter powered dc motor system [2]

TABLE I
PARAMETERS OF THE BUCK-CONVERTER POWERED DC MOTOR

Parameter	Value	Unit
L_M	8.9×10^{-3}	H
R_M	6	Ω
K_E	0.0517	V-s/rad
K_M	0.0517	N-m/A
J_M	7.95×10^{-6}	kg-m^2
U_e	24	V
L	1.33×10^{-6}	H
R_L	0.2	Ω
C	470×10^{-6}	F

B. Numerical results

Consider a buck-converter powered dc motor system as a plant G with its mathematical model in (9). Although the model is given, it is important to stress that our proposed method did not use any knowledge of the model to design the controller. The system parameters is depicted in Table I, which are obtained from [2]. Next, we employ a smooth desired trajectory tracking of angular velocity given by

$$r(t) = 75(\tanh(30(t-0.1))+1), \quad t_0 \le t \le t_f, \qquad (10)$$

which is same as the desired trajectory tracking reported in [9]. The corresponding design parameters of sigmoid-based PI controller $K_{PI}(s)$ are tabulated on Table II. The objective is to find $\boldsymbol{z} \in \mathbb{R}^8$, which minimizes the objective function J in (4) for $w_1 = 10$ and $w_2 = 1$, $t_0 = 0$ and $t_f = 0.25$. Based on preliminary experiments, we select the gains of the GSPSA based algorithm as $\hat{a}(k) = 0.2/(k+21)^{0.5}$, $\hat{c}(k) = 0.005/(k+1)^{0.101}$, $\hat{b}(k) = 0.005/(((k+1)^{0.5})\ln((k+1)^{0.5}+1000))^{0.5}$, and $k_{\max} = 250$. The random vector $\boldsymbol{r}_1(k) \in \mathbb{R}^8$ is generated based on the Bernoulli distribution

$$\begin{cases} \mathbb{P}(r_{1i}(k) = -1) = 1/2, \\ \mathbb{P}(r_{1i}(k) = 1) = 1/2, \end{cases} \qquad (11)$$

and $r_{1i}(k)$, $(i = 1, 2, \ldots, 8)$ is its ith component. Meanwhile, each element of $r_{2i}(k)$, $(i = 1, 2, \ldots, 8)$ is randomly selected from the uniform distribution on the interval $(0, 1)$. We assume that the initial design parameter $\boldsymbol{z}(0)$ as presented in Table II provides a stable closed-loop system during interval $[t_0, t_f]$.

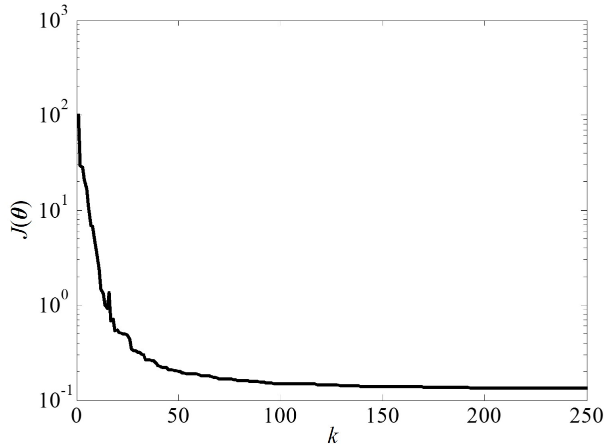

Fig. 3. Response of the objective function

Figure 3 depicts the objective function response for 250 iterations while Table II depicts the optimum design parameters $\boldsymbol{z}^* \in \mathbb{R}^8$. These results clarify the effectiveness of GSPSA-based method in minimizing the objective function and produces optimal sigmoid-based PI parameters.

Furthermore, the $y(t)$ and $u(t)$ responses are demonstrated in Figures 4 and 5, respectively. Here, both of the responses are compared with other existing results, which are conventional PI [8] and PI-Fuzzy [9]. In these figures, the dot black line represents the reference, the thick grey line represents PI controller, the dash black line represents the PI-Fuzzy controller and the thick black line represents the sigmoid-based PI controller. It demonstrates that the data-driven sigmoid-based PI achieves better angular trajectory tracking as compared to PI and PI-Fuzzy. In particular, the proposed data-driven sigmoid-based PI provides closer angular velocity response to the reference $r(t)$ with smoother tracking than PI and PI-Fuzzy as shown in Figure 4. This fact is also supported from $\int_{t_0}^{t_f} e(t)^2 dt$ values in Table III. Here, we can clearly see that the data-driven sigmoid-based PI controller produces a slightly smaller values of $\int_{t_0}^{t_f} e(t)^2 dt$ than other controllers during the given time interval.

Meanwhile, the control input $u(t)$ response of each controller shows a similar correlation with the obtained angular velocity response. In particular, the PI-Fuzzy and data-driven sigmoid PI achieve higher duty cycle than PI during transient response to provide better angular tracking. This fact is also proven from $\int_{t_0}^{t_f} u(t)^2 dt$ values in Table III. It shows that the control input energy of PI controller still not enough to regulate the angular tracking error. However, PI and data-driven sigmoid PI obtain more smooth duty cycle than PI-Fuzzy during steady state response. Here, we can clearly see that data-driven sigmoid PI controller produces slightly better control input than other controllers during the given time interval. Thus, we can confirm that the proposed PI parameters that are varied based on sigmoid function of angular velocity error has a good potential in improving the control performance of

TABLE II
SIGMOID-PI PARAMETERS

θ	**Sigmoid-PI parameters**	$z(0)$	**θ computes from $z(0)$**	z^*	**θ^* computes from z^***
θ_1	$K_{P\min}$	−2.1612	0.0069	−1.5200	0.0302
θ_2	Δ_P	0.0000	1.0000	−0.0210	0.9528
θ_3	$K_{I\min}$	−0.4014	0.3968	0.9563	9.0425
θ_4	Δ_I	0.0000	1.0000	0.6434	4.3998
θ_5	α_P	1.0000	10.0000	1.4353	27.2438
θ_6	α_I	1.0000	10.0000	0.9303	8.5165
θ_7	β_P	1.0000	10.0000	1.0166	10.3906
θ_8	β_I	1.0000	10.0000	−0.6022	0.2499

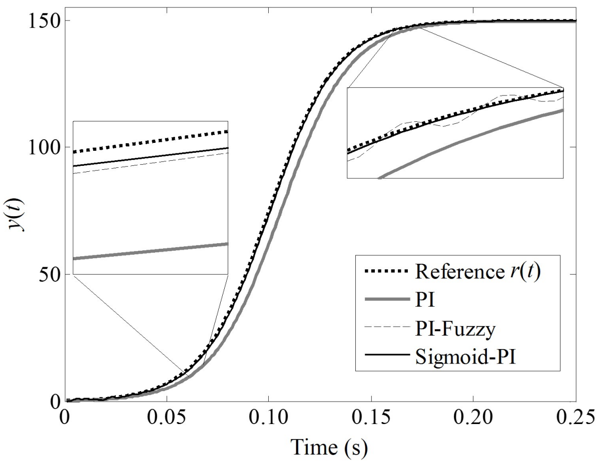

Fig. 4. Angular velocity responses

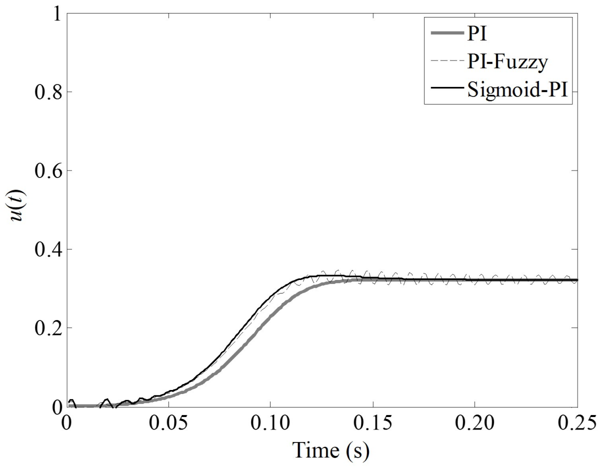

Fig. 5. Duty cycle responses

buck converter powered dc motor system.

TABLE III
PERFORMANCE INDEX COMPARISON

Controller	**PI [8]**	**PI-Fuzzy [9]**	**Sigmoid-PI**
$\int_{t_0}^{t_f} e(t)^2 dt$	6.5190	0.0338	0.0278
$\int_{t_0}^{t_f} u(t)^2 dt$	0.0156	0.0162	0.0162

V. CONCLUSION

In this paper, we presents a performance investigation of a novel data-driven sigmoid-based PI for angular velocity trajectory tracking of buck-converter powered dc motor. The proposed method is validated on a buck-converter powered dc motor model in [2]. The numerical example results show that the data-driven sigmoid-based PI, which is tuned using global simultaneous perturbation stochastic approximation, yields a better angular velocity tracking as compared to conventional PI and PI-Fuzzy. In particular, by adopting PI parameters that are varied based on sigmoid function of angular velocity error, it provides the lowest angular tracking error with smooth angular velocity and duty cycle responses. Thus, we can confirm the superiority of the data-driven sigmoid-based PI in angular velocity tracking performance of buck-converter powered dc motor.

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