Estimating Parameter Deviation of DC Motor using Sliding-Mode Observer and Least-Square Algorithm

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***Abstract*—Performing system/plant maintenance is very important as an attempt to avoid any failure during system/plant operation. One of the methods that can be adopted to detect any potential failure inside a plant is by estimating the value of the plant's parameters. When the plant's parameters deviate too far from their nominal values, the plant will be more likely to fail. In this paper, an estimation method for estimating the deviation in the parameters of a linear system/plant is proposed as an improvement of the previously proposed method. The main component of this parameter deviation estimator system was an observer block which adopted the sliding-mode observer in combination with an adaptive filter block. The adaptive filter block used in this system adopted the least-square algorithm instead of adopting the gradient-descent algorithm as in the previously proposed method. This method was simulated to estimate the deviation in the parameters of DC motor to verify the effectiveness of the proposed metho. The simulation results showed that this method could successfully estimate the deviation of DC motor parameters with a maximum estimation error of less than 4 %. This method could estimate the deviation in DC motor parameters for both constant deviation value and slowly-changing deviation value as time goes by. In addition, estimating the parameter deviation using this method could produce a good level of accuracy even when using a fairly low-frequency input signal. This method is suitable to be adopted in parameter monitoring process of a linear system so that any fault occurring in the system can be detected and isolated before the plant is fatally damaged.**

***Keywords*— Sliding-Mode Observer, Parameter Deviation, Least-Square Algorithm, Linear System, DC Motor.**

I. INTRODUCTION

Performing system/plant maintenance is essential to ensure the continuity of the plant operation. Any damage that occurs inside the plant can disrupt its operation. If the damage inside the plant is too severe, it can stop the plant's operation completely. Obviously, it is not a good thing, especially for industrial plants. When the plant is fatally damaged, it can stop the whole production process, causing significant losses in both cost and time for the industry. Furthermore, when a plant has been fatally damaged, the cost required for the repair process will be more expensive, aggravating the financial loss experienced by the industry.

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[Received: 10 July 2022, Revised: 2 November 2022]

A maintenance process performed after the plant has been damaged is known as reactive maintenance [1]. There is also another type of maintenance that is done periodically. However, a plant with a heavy workload is often damaged before the maintenance process is conducted, as the components inside the plant degrade faster than expected. In other words, fatal damage to the plant can occur without being discovered beforehand. To overcome this problem, a continuous monitoring process is required so that any potential damage inside the plant can be detected early and anticipation can be made before the plant is fatally damaged.

There have been several reported works on the maintenance process using statistical data as their foundations [2]-[4]. However, recent development indicates that the model-based maintenance has become a more popular method to be adopted [5]-[12]. Using the mathematical model of the plant as the foundation, it offers a wider range of problems that can be solved. The model-based maintenance can also be adopted to identify the fault's location inside the plant. For example, the methods for detecting a fault related to the plant's input (actuator fault signal detection) have been proposed in [13]-[16], whereas the methods for detecting a fault related to the plant's output (sensor fault signal detection) have been proposed in [17]-[20]. Other than in actuator (input) and sensor (output), the fault might also occur inside the plant due to the deviation of the plant's parameters from their nominal values. This deviation might occur because of the continuous operation of the plant, triggering the deviation in the plant's parameters value. The deviation of the plant's parameter value is generally a slow process. However, as time passes, it might deviate too far from the nominal, hence increasing the possibility of any fatal damage occurring inside the plant. Therefore, an estimation method for estimating the deviation of the plant's parameters from their nominal values is necessitated. With the existence of this estimation method, it is expected that any fault inside the plant can be detected early before it causes fatal damage to the plant.

The main goal of the research discussed in this paper is to estimate the deviation of plant parameters from their nominal values. The estimation process was performed by combining the method for reconstructing the actuator fault signal using a sliding-mode observer (SMO) and an estimation method adopting the least-square algorithm for estimating the deviation of the plant's parameters from their nominal values based on the previously obtained actuator fault signal. The estimation method proposed in this paper is an improvement of the method proposed in [21]. The main difference is the adoption of the least-square algorithm instead of the gradient-descent algorithm, as in [21]. The adoption of the least-square algorithm is expected to give a more accurate estimation result even when using a fairly low-frequency input signal.

This paper is written in the following arrangement. First, some literature reviews relating the mathematical model of a plant with actuator fault, reconstruction of actuator fault signal using SMO, and estimation method of plant's parameter deviation proposed in [21] will be explained in Section II. Next, the explanation regarding the mathematical model of DC motor followed by the explanation on the proposed estimation method for estimating the deviation of DC motor parameters will be presented in Section III. For verifying the effectiveness of the proposed method, some explanations regarding the setup of the simulations and their results will be explained in Section IV. Finally, some concluding remarks will be given in Section V.

II. Actuator Fault and Parameter Deviation Estimation

A. *Mathematical Model of Plant with Actuator Fault*

A linear time-invariant (LTI) system can be modeled using a state equation as shown in the following equations.

$$\dot{x}(t) = Ax(t) + Bu(t) \tag{1}$$

$$y(t) = Cx(t) \tag{2}$$

where $x \in \mathbb{R}^n$, $u \in \mathbb{R}^m$, and $y \in \mathbb{R}^p$ are defined as the state vector, input vector, and output vector of the plant, respectively; n, m, and p are defined as the number of states, inputs, and outputs of the plant, respectively. The value of matrices $A \in \mathbb{R}^{n\times n}$, $B \in \mathbb{R}^{n\times m}$, and $C \in \mathbb{R}^{p\times n}$ will determine the plant's characteristics. Suppose that a disturbance exists on the plant's actuator, the plant can be modeled using the following mathematical equation.

$$\dot{x}(t) = Ax(t) + Bu(t) + \mu(t) \tag{3}$$

$$y(t) = Cx(t) \tag{4}$$

where $\mu \in \mathbb{R}^n$ is defined as the disturbance vector due to the existence of the disturbance on the plant's actuator [14], [15].

For this plant, the value of the state vector $x(t)$ can be estimated using an observer system whose dynamics is described by the following equation

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + F[y(t) - C\hat{x}(t)] \tag{5}$$

to replicate the dynamics of the original plant that is going to be estimated, with $F \in \mathbb{R}^{n\times p}$ is defined as the gain matrix of the observer system. This kind of observer system is generally known as Luenberger observer [22]. Suppose that a new variable $e(t)$ is defined, its value is defined as the following.

$$e(t) = x(t) - \hat{x}(t). \tag{6}$$

This variable is known as the state estimation error which represents the difference between the value of the state vector $\hat{x}(t)$ estimated by the observer, and the actual state vector value $x(t)$ of the original plant. From (3)-(6), the dynamics of $e(t)$ can be described by the following equation.

$$\dot{e}(t) = (A - FC)e(t) + \mu(t). \tag{7}$$

If the plant does not experience any disturbance on its actuator ($\mu = 0$), therefore $e \to 0$ when $t \to \infty$, if the eigenvalues of matrix $(A - FC)$ are all stable. As a result, the estimated state vector value $\hat{x}(t)$ will be the same as the actual state vector value $x(t)$.

However, the circumstances will be different when the plant experiences an actuator fault. As can be seen in (7), due to the presence of actuator fault $\mu(t)$, the value of $e(t)$ cannot reach zero when $t \to \infty$, even though the eigenvalues of matrix $(A - FC)$ are all stable. Consequently, the actual state vector value $x(t)$ cannot be properly estimated by this observer system. Therefore, an observer system that can suppress the effect of the actuator fault signal and have capabilities to reconstruct the actuator fault signal is needed so that the overall performance can be improved.

B. *Reconstruction of Actuator Fault Signal using Sliding-Mode Observer (SMO)*

The sliding-mode is a control system method that utilizes a switch control law technique to force and maintain the state vector of a system within a predefined condition [20]. This method is also adopted for an observer system to force and maintain the value of the state estimation error $e(t)$ so that it is always equal to zero. This type of observer is hence known as an SMO.

The dynamics of SMO can be described using the following equation.

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + G\nu\left(e_y(t)\right) \tag{8}$$

where

$$e_y(t) = y(t) - C\hat{x}(t) \tag{9}$$

is defined as the output estimation error, $\nu \in \mathbb{R}^p$ is defined as the control signal whose value depends on the value of output vector $y(t)$ and the estimated state vector value $\hat{x}(t)$, and $G \in \mathbb{R}^{n\times p}$ is defined as the gain matrix of the SMO system. Consider a special plant whose characteristics are defined as follows.

$$n = p \tag{10}$$

$$C = G = I_n \tag{11}$$

where I_n is defined as an identity matrix with the size of $n \times n$. Equation (10) indicates that the number of plant's output (p) is equal to its number of state (n) of this system, whereas (11) indicates that all states of this system are measurable, and they become the output of this plant.

Using this information, (8) can now be written as follows

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + \nu\left(e(t)\right) \tag{12}$$

by assuming that $G = I_n$. From (3), (6) and (12), the dynamics of state estimation error value of this observer can be obtained, as shown in the following equation.

$$\dot{e}(t) = Ae(t) + \mu(t) - \nu\left(e(t)\right). \tag{13}$$

The main idea of a SMO is by generating control signal ν based on the value of $e(t)$ as follows.

$$v(t) = -\rho \frac{e(t)}{|e(t)|} = -\rho\, sign\big(e(t)\big) \quad (14)$$

where ρ is defined as the amplitude of control signal v. The control signal defined in (14) can force and maintain the $e(t)$ value to be equal to zero. Because of that, as the value of $e(t)$ is forced and maintained to have a constant value (zero value), then $\dot{e}(t) = 0$. Using this information, then it can be proved from (13) that

$$v(t) = \mu(t) \quad (15)$$

indicating that the control signal $v(t)$ in SMO always tries to suppress the effect of actuator fault signal $\mu(t)$ so that the value of $e(t)$ can always be maintained to be equal to zero. In addition to that, (15) also indicates that the actuator fault signal $\mu(t)$ can be reconstructed by observing the shape of control signal $v(t)$. This information can be utilized in identification and isolation process of the actuator fault occurring in a plant. This information can also be utilized for estimating the parameter deviation of a plant as will be explained in Section II. C.

C. *Estimation Method of Plant's Parameter Deviation*

As time goes by, the parameters of a plant might deviate from their nominal values. Several factors, such as the environment, temperature, and condition of the place where the plant is located, might contribute to this parameter deviation. As the result, the value of state matrix A and input matrix B in the state equation shown in (1) might also deviate from their nominal values.

Suppose that the value of matrices A and B in (1) are defined as follows.

$$A = A_o + \Delta A \quad (16)$$

$$B = B_o + \Delta B \quad (17)$$

where A_o, B_o are the initial values of matrices A and B, respectively; and $\Delta A, \Delta B$ are the deviation from their initial values. As the result, the state equation can now be written as follows.

$$\dot{x}(t) = A_o x(t) + B_o u(t) + \mu_\Delta(t) \quad (18)$$

where

$$\mu_\Delta(t) = \Delta A x(t) + \Delta B u(t) = W z(t) \quad (19)$$

is defined as the actuator fault signal due to the deviation of plant's parameters, where

$$W = [\Delta A \quad \Delta B] \quad ; \quad z(t) = \begin{bmatrix} x(t) \\ u(t) \end{bmatrix}. \quad (20)$$

Adopting the SMO for this case, the dynamics of SMO can now be described as follows

$$\dot{\hat{x}}(t) = \big(A_o + \Delta\hat{A}\big)\hat{x}(t) + \big(B_o + \Delta\hat{B}\big)u(t) + (A_{obs} - A_o)e(t) + v\big(e(t)\big) \quad (21)$$

so that the dynamics of state estimation error can be written as

$$\dot{e}(t) = (A_{obs} + \Delta A)e(t) + e_W \hat{z}(t) - v\big(e(t)\big) \quad (22)$$

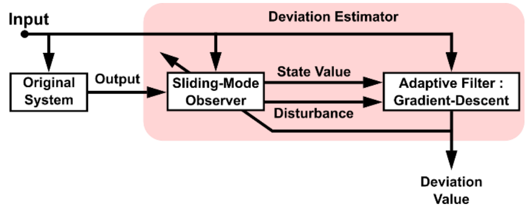

Fig. 1 Parameter deviation estimator system adopting gradient-descent algorithm.

where

$$e_W = \big[\big(\Delta A - \Delta\hat{A}\,\big) \quad \big(\Delta B - \Delta\hat{B}\,\big)\big] = W - \widehat{W} \quad (23)$$

$$\hat{z}(t) = \begin{bmatrix} \hat{x}(t) \\ u(t) \end{bmatrix} \quad (24)$$

and $\Delta\hat{A}, \Delta\hat{B}$ are defined as the estimated deviation value of the plant's parameters. Whereas matrix A_{obs} can be selected to adjust the poles of this state equation. From (22), it can be seen that during steady-state condition, the following relation is satisfied:

$$v(t) = e_W \hat{z}(t), \quad (25)$$

indicating that the control signal $v(t)$ contains the information regarding the estimation error of the parameter deviation matrices ΔA and ΔB. Then, this signal can be utilized to estimate the value of parameter deviation matrices ΔA and ΔB [21].

This estimation process can be performed using a system shown in Fig. 1. The information regarding the value of state vector, input vector, and the reconstructed fault signal are sent and processed by an adaptive filter to estimate the value of parameter deviation matrices ΔA and ΔB. In [21], the estimation process is performed by adopting gradient-descent algorithm described by the following equation.

$$\widehat{W}_k = \widehat{W}_{k-1} + \Lambda \hat{z}_k v_k^T \quad (26)$$

where $\widehat{W}_k$ is the estimated parameter deviation value at time index k, $\hat{z}_k = \hat{z}(kT_s)$, $v_k = v(kT_s)$, $\Lambda \in \mathbb{R}^n$ is defined as the step-size matrix, and T_s is the sampling period of this estimation process.

The gradient-descent algorithm can successfully perform the estimation process with good accuracy. However, the accuracy of this estimation result strongly depends on the input signal given to this plant. This system can produce an accurate estimation result when the plant is given an input signal whose frequency is beyond the cut-off frequency of the plant. Unfortunately, sometimes this kind of input signal might be inappropriate because it increases the possibility of triggering any damage in the plant. For that reason, a better estimation algorithm is needed so that the estimation process can produce a more accurate result without requiring this kind of high frequency input signal.

III. ESTIMATING PARAMETER DEVIATION OF DC MOTOR

A. *Mathematical Model of Plant DC Motor*

A DC motor can be modelled using the model of the LTI system. This model consists of two coupled differential equations which represents the characteristics of a DC motor [23]. The first equation represents the dynamics of current I_a flowing through the armature of the DC motor. Applying Kirchhoff voltage law, then the following equation can be obtained.

$$\dot{I}_a(t) = -\left(\frac{K_b}{L}\right)\omega(t) - \left(\frac{R}{L}\right)I_a(t) + \left(\frac{1}{L}\right)e_a(t) \qquad (27)$$

where L, R, and e_a are defined as the inductance, resistance, and input voltage of the armature, respectively, whereas K_b and ω are defined as the back-emf constant and the rotor angular velocity, respectively. Then, the second equation represents the dynamics of rotor angular velocity ω based on Newton's second law as shown in the following equation

$$\dot{\omega}(t) = -\left(\frac{B_v}{J}\right)\omega(t) + \left(\frac{K_t}{J}\right)I_a(t) \qquad (28)$$

by assuming that there is no external torque acting on the rotor. In equation (28), B_v, J, and K_t are defined as the viscous friction constant, moment of inertia, and torque constant of the motor, respectively.

From (27) and (28), then a DC motor can be represented using a state equation shown in (1) with $x(t)$, A, and B are defined as follows

$$x(t) = \begin{bmatrix}\omega(t)\\ I_a(t)\end{bmatrix} \;\; ; \;\; A = \begin{bmatrix}-\frac{B_v}{J} & \frac{K}{J}\\ -\frac{K}{L} & -\frac{R}{L}\end{bmatrix} \;\; ; \;\; B = \begin{bmatrix}0\\ \frac{1}{L}\end{bmatrix} \qquad (29)$$

by assuming that $K_i = K_t = K$. From (29), in the case when the value of state matrix A and input matrix B are known, then the DC motor parameters can also be calculated as follows.

$$L = \frac{1}{b_{21}} \qquad (30)$$

$$R = -a_{22}L = -\frac{a_{22}}{b_{21}} \qquad (31)$$

$$K = -a_{21}L = -\frac{a_{21}}{b_{21}} \qquad (32)$$

$$J = \frac{K}{a_{12}} = -\frac{a_{21}}{a_{12}b_{21}} \qquad (33)$$

$$B_v = -a_{11}J = \frac{a_{11}a_{21}}{a_{12}b_{21}} \qquad (34)$$

where a_{ij} and b_{ij} are the entry in ith row and jth column of matrices A and B, respectively. From (30)-(34), it can be seen that the value of DC motor parameters can be estimated from the estimated value of matrices A and B of the DC motor. This concept becomes the basic idea of the method for estimating the parameter deviation of DC motor proposed in Section III. B.

B. Proposed Estimation Method

Generally, parameter deviation in a plant is not a rapid process but a slow process that occurs over a long period. Because of that, the process of estimating the parameter deviation does not have to be performed continuously; rather, it can be carried out periodically with a relatively not-too-rapid time interval, viz., every minute, every hour, or even once a day. This time interval can be selected based on how significant this parameter deviation affects the plant's overall performance. On the other hand, getting an accurate estimation result becomes the most crucial thing in this estimation process so that accurate information regarding the plant's condition can be obtained.

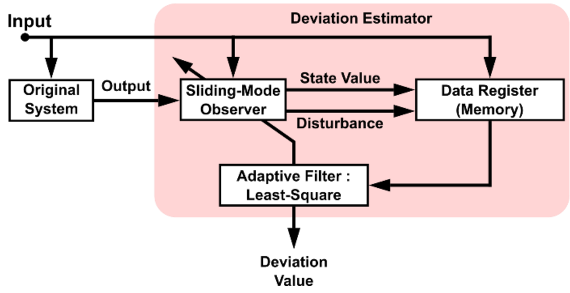

Fig. 2 Proposed parameter deviation estimator system adopting the least-square algorithm.

The adoption of the gradient-descent algorithm in [21] has the advantage of enabling the estimation process to be performed continuously with a rapid time interval while still having a low computational load. However, the accuracy generated by this algorithm is not particularly good. For this reason, in this paper, the least-square algorithm is proposed as a replacement for the gradient-descent algorithm. The estimation process adopting the least-square algorithm was performed using the following equations.

$$\widehat{W}_k = \widehat{W}_{k-1} + \left(\hat{Z}_k\hat{Z}_k^T\right)^{-1}\left(\hat{Z}_kV_k^T\right) \qquad (35)$$

where

$$\hat{Z}_k = \left[\hat{z}_{k,(N-1)} \;\; \hat{z}_{k,(N-2)} \;\; \ldots \;\; \hat{z}_{k,1} \;\; \hat{z}_{k,0}\right] \qquad (36)$$

$$V_k = \left[v_{k,(N-1)} \;\; v_{k,(N-2)} \;\; \ldots \;\; v_{k,1} \;\; v_{k,0}\right] \qquad (37)$$

$$\hat{z}_{k,s} = \hat{z}(kT_s - sT_d) \;\; ; \;\; v_{k,s} = v(kT_s - sT_d). \qquad (38)$$

In (36)-(38), N is defined as the length of the data included for this estimation process, whereas T_d is defined as the sampling period of this estimator system. The block diagram of the proposed parameter deviation estimator using the least-square algorithm is shown in Fig. 2.

The least-square algorithm involves the process of computing an inverse of a matrix, as indicated by (35). As a result, the least-square algorithm has a higher computational load than the gradient-descent algorithm. However, in terms of accuracy, the least-square algorithm can produce a more accurate estimation result than that of the gradient-descent algorithm. Therefore, it is very suitable to adopt the least-square algorithm for estimating the deviation of the plant's parameter with slow-changing characteristics yet requires a high degree of accuracy.

IV. Simulation Results and Discussion

A. Selecting DC Motor Parameter for Simulation

As a process to verify the effectiveness of the estimation method proposed in Section III. B, the performance of the proposed estimation method was simulated adopting DC motor system as the plant. The DC motor parameters in this

TABLE I
DATASHEET OF THE SELECTED DC MOTOR FOR SIMULATION

Symbol	Parameter	Value	Unit
P	Mechanical Power	579	kW
U	Input Voltage	460	V
I	Armature Current	1340	A
n_{rpm}	Rotor Angular Velocity	835	rpm
L	Armature Inductance	0.25	mH
R	Armature Resistance	19	mΩ
τ	Torque	6625	N.m
J	Moment of Inertia	28.3	kg.m^2

TABLE II
PARAMETER VALUE OF THE SELECTED DC MOTOR FOR SIMULATION

Symbol	Parameter	Value	Unit
B_v	Viscous Friction Constant	75.8	N.m/(rad/s)
K_t	Torque Constant	4.94	N.m/A
K_b	Back-emf Constant	4.97	Volt/(rad/s)
L	Armature Inductance	0.25	mH
R	Armature Resistance	19	mΩ
J	Moment of Inertia	28.3	kg.m^2

simulation was obtained from datasheet of a DC motor whose power capacity was more than 570 kW [24], as shown in Table I.

Using the datasheet shown in Table I, the value of parameters L, R, and J of this DC motor can be obtained directly. Meanwhile, parameters B_v, K_t, and K_b could be calculated using the following equations.

$$B_v = \frac{\tau}{\omega_m} \tag{39}$$

$$K_t = \frac{\tau}{I} \tag{40}$$

$$K_b = \frac{U - IR}{\omega_m} \tag{41}$$

where

$$\omega_m = 2\pi\left(\frac{n_{rpm}}{60}\right). \tag{42}$$

Using (39)-(42), then the parameter value of the DC motor could be calculated, and the result is shown in Table II.

Using the parameter value shown in Table II, the value of matrices A and B in this simulation could be calculated as follow.

$$A = \begin{bmatrix} -2.68 & 0.175 \\ -1.98 \times 10^4 & -76.0 \end{bmatrix} \;;\; B = \begin{bmatrix} 0 \\ 4000 \end{bmatrix} \tag{43}$$

B. Estimating Parameter of DC Motor

This section discusses the simulation to demonstrate the process of estimating the value of DC motor parameters using the proposed method. This simulation was started by initializing the value of matrices A and B (A_o and B_o) as follows

$$A_o = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \;;\; B_o = \begin{bmatrix} 0 \\ 0 \end{bmatrix}. \tag{44}$$

At the end of simulation, the deviation matrices ΔA and ΔB were expected to have the value of the following:

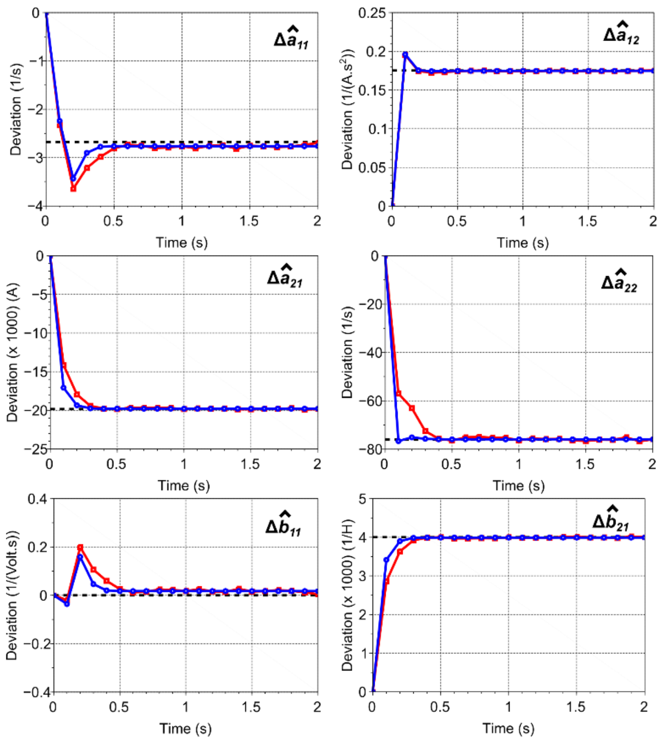

Fig. 3 The value of estimated deviation matrices $\Delta\hat{A}$ and $\Delta\hat{B}$ as a function of time with 10 Hz sinusoidal input signal, without (blue-circle) and with (red-square) additional noise.

$$\Delta A = \begin{bmatrix} -2.68 & 0.175 \\ -1.98 \times 10^4 & -76.0 \end{bmatrix} \;;\; \Delta B = \begin{bmatrix} 0 \\ 4000 \end{bmatrix} \tag{45}$$

which are equal to the value of matrices A and B as shown in (43), respectively.

The simulation was performed using a RK4 (4th Order Runge-Kutta) ordinary differential equations (ODE) solver method. The poles of this plant were located at $s = -39.3 \pm j46.1\ rad/s$, so that $|s| = 60.6\ rad/s$. Since this DC motor plant is a continuous time system, the sampling period T_{samp} of this simulation was selected to be $T_{samp} < 1/(100|s|)$ so that this simulation could maintain the continuous-time characteristics of this system. Smaller T_{samp} value leads to a more accurate simulation result with the price of heavier computational load. By considering the balance between accuracy and computational load, the sampling period of simulation process was selected to be $T_{samp} = 50\ \mu s$.

Fig. 3 shows the value of estimated deviation matrices $\Delta\hat{A}$ and $\Delta\hat{B}$ as a function of time when the DC motor system is given a sinusoidal input signal with frequency $10\ Hz$, with and without additional noise. Fig. 3 demonstrates that the value of deviation matrices ΔA and ΔB can be estimated successfully using the proposed estimation method. Furthermore, when the input signal of this system was contaminated with noise, the estimation of deviation matrices ΔA and ΔB could still be performed successfully. Further investigation is still necessitated to learn about the capability of this estimation method in performing the estimation process when the DC motor is contaminated with a stronger noise signal.

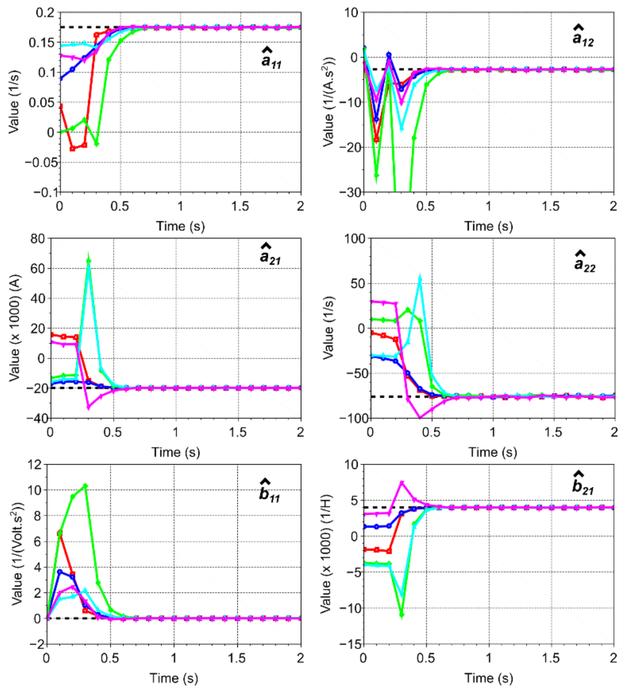

Fig. 4 Estimated value of matrices A and B ($\hat{A}$ and $\hat{B}$) as a function of time for various initial values A_o and B_o.

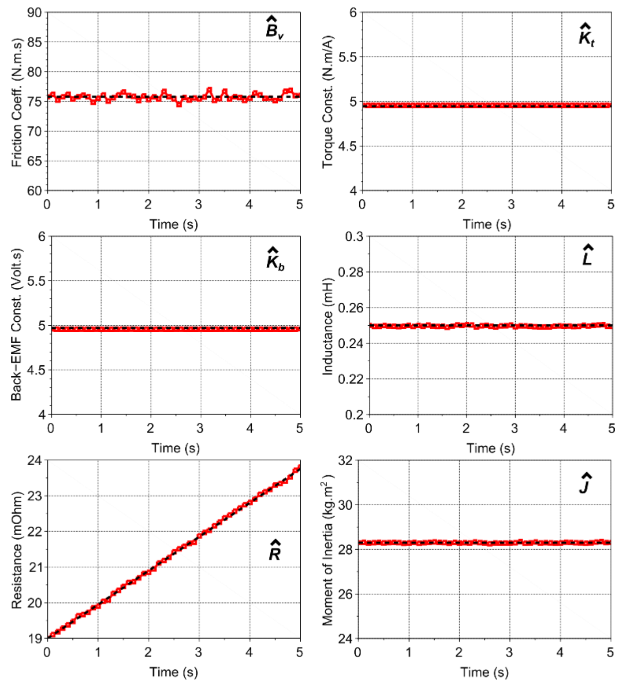

Fig. 5 Estimated DC motor parameters values for scenario I.

TABLE III
COMPARISON BETWEEN THE ESTIMATED DC MOTOR PARAMETERS VALUES AND THEIR ACTUAL VALUES

Symbol	Estimated Value	Actual Value	Unit	Error (%)
$\hat{B}_v$	78.4	75.8	N.m/(rad/s)	3.43
$\hat{K}_t = \hat{K}$	4.96	4.94	N.m/A	0.31
$\hat{K}_b = \hat{K}$	4.96	4.97	V/(rad/s)	0.20
$\hat{L}$	24.9	0.25	mH	0.25
$\hat{R}$	19.2	19	mΩ	1.32
$\hat{J}$	28.4	28.3	kg.m^2	0.28

In addition to that, this estimation method could perform the estimation process successfully with initial values of A_o and B_o, other than the values shown in (44). Fig. 4 shows the estimated value of matrices A and B ($\hat{A}$ and $\hat{B}$) as a function of time for various initial values A_o and B_o. Furthermore, based on Fig. 4, the estimation results of all the elements of matrices A and B successfully converge to their actual values for all initial values of A_o and B_o.

Table III shows the estimated value of the DC motor parameters which are obtained from the estimation result of matrices A and B ($\hat{A}$ and $\hat{B}$). From the comparison between the estimated DC motor parameters values and their actual values in Table III, the estimation process of the DC motor parameters could be performed well using the proposed method. It is supported by the fact that the estimated value of the DC motor parameters was quite close to their actual values, with an estimation error for most of the parameters below 0.5% and a maximum estimation error of less than 3.5%.

As has been explained before, the poles of the DC motor system in this case were located at $|s| = 60.6\, rad/s \approx 10\, Hz$, indicating that the cut-off frequency of this system was approximately around 10 Hz. Nevertheless, the estimation process of the DC motor parameters using the proposed method could still generate a very good accuracy. This result shows that adopting the least-square algorithm can produce an estimation result with good accuracy, even when using a fairly low-frequency input signal.

TABLE IV
TEST SCENARIO OF DC MOTOR PARAMETERS ESTIMATION

Scenario	Condition	Description
I	$R \uparrow$	Increase in armature resistance value.
II	$B_v \uparrow$	Increase in the value of viscous friction constant.
III	$B_v \uparrow$ and $J \uparrow$	Increase in the value of viscous friction constant and the total moment of inertia (rotor and load).

C. Estimating Parameter Deviation of the DC Motor

As has been explained before, as time goes by, the value of DC motor parameters might deviate from their nominal values. This deviation is generally a slow process. The estimation method proposed in this paper is also expected to estimate this kind of deviation. Therefore, based on this estimation result, the maintenance process can be performed before DC motor plant is fatally damaged.

In this test, three different scenarios, as shown in Table IV, were used. Scenario I simulates the case when there is an increase in the value of armature resistance R, which might occur because of an increase in armature temperature. Scenario II simulates the case when there is an increase in the value of the viscous friction constant B_v. Finally, scenario III simulates the case when there is an increase in the value of viscous friction constant B_v, which simultaneously there is also an

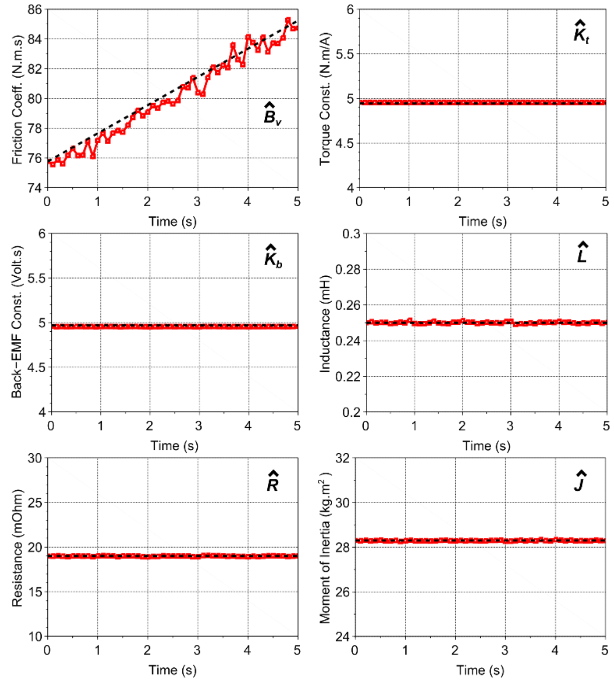

Fig. 6 Estimated DC motor parameters values for scenario II.

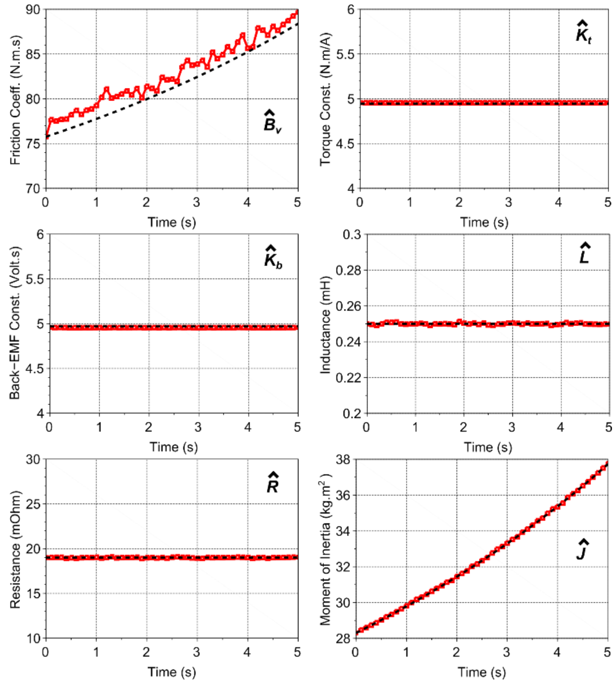

Fig. 7 Estimated DC motor parameters values for scenario III.

increase in the value of the moment of inertia J which might occur when the rotor is connected to an external load.

Fig. 5, Fig. 6, and Fig. 7 show the estimated DC motor parameter values for the scenarios I, II, and III, respectively. According to Fig. 5, the increase in R value can be well estimated by the proposed estimation method. In Fig. 6, it can also be seen that the increase in B_v value can be well estimated. Although in terms of accuracy it is not as good as the estimation result of R value in Scenario I, the proposed estimation method is still able to track the change in the B_v value. Finally, for Scenario III, the increase in both B_v and J values can also be estimated well, as shown in Fig. 7.

TABLE V
MAXIMUM ESTIMATION ERROR IN THE ESTIMATION RESULT OF THE DC MOTOR PARAMETERS

Scenario	Maximum Estimation Error (%)					
	B_v	K_t	K_b	L	R	J
I	1.75	0.28	0.27	0.42	0.33	0.18
II	1.76	0.27	0.29	0.58	0.54	0.15
III	3.72	0.28	0.29	0.54	0.57	0.27

In addition, the graphs shown in Fig. 5, Fig. 6, and Fig. 7 show that the estimated value of the other parameters is still constant. This fact indicates that in the proposed estimation method, any deviation in a parameter does not significantly affect the estimation result of other parameters.

Table V shows the maximum estimation error value for each DC motor parameter for scenarios I, II, and III. From this simulation result, the accuracy of the estimated DC motor parameters values obtained using the proposed estimation method was very good, with the highest estimation error value still less than 3.8 %.

V. CONCLUSIONS

An estimation method for estimating the deviation in the parameters of a linear system has been proposed as an improvement of the previously proposed method. This method adopted the least-square algorithm as the parameter deviation estimation algorithm implemented inside the adaptive filter block. This method was simulated to estimate the deviation in the DC motor parameters to verify the proposed method's effectiveness. The simulation results showed that this method could successfully estimate the deviation of DC motor parameters with a maximum estimation error of less than 4 %. This method could estimate the deviation in DC motor parameters for both constant deviation values and slowly-changing deviation values over time. In addition, estimating the parameter deviation using this method could produce a good accuracy level even when using a fairly low-frequency input signal. This method is suitable to be adopted in the parameter monitoring process of a linear system so that any fault that occurs in the system can be detected and isolated before the plant is fatally damaged.

CONFLICT OF INTEREST

The authors declare that this research was conducted and written with no conflict of interest.

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