Power Electronics and Drives
Volume 4(39), 2019 DOI: 10.2478/pead-2019-0017

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Power Electronics and Drives

Design of Observer-Based Fault Detection Structure for Unknown Systems using Input–Output Measurements: Practical Application to BLDC Drive

Research Article

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Received February 17, 2019; October 04, 2019

Abstract: Industrial systems serve us in all areas of life. Faults may result in economic loss and wasting energy. Detecting the onset of faults, and determining their location are important engineering tasks. An important class of fault detection (FD) and diagnosis methods utilizes the mathematical model of the monitored system. But, the parameters required for mathematical modelling are limited or unavailable for the most real industrial engineering applications. Observer-based FD is one of the main approaches to FD and identification. At the same time, the traditional observer's gain calculation required system model parameters. So, this article presents the design of a novel observer for FD purposes using the input–output measurements of the system with unknown parameters. This proposed observer's design considers observer's gain tuning, regardless of the mathematical representation of the plant. This the new feature that distinction our observer will facilitate the implementation of FD systems for many unknown parameters industrial systems. The effectiveness of the proposed observer is verified by experimental application to BLDC motor and compared with classical Luenberger observer. The experimental and comparison results prove feasibility and effectiveness of the proposed observer for FD purposes.

Keywords: *fault • sensor • measurements • observer • BLDC motor*

1. Introduction

Fault and failure are not the same, as the system may run with fault, but system failure will interrupt its operation. The fault is the unpermitted deviation of one system or a component parameter from the normal condition (Isermann, 2006). The fault may yield to either system's complete failure, decreasing system efficiency or overall system lifetime and wasting energy. Furthermore, the fault may lead to destruction at the physical components of the system. Supervisory functions indicate undesired process states to help in maintenance and damage limitation avoidance. Supervisory functions include monitoring, automatic protection and supervision with fault diagnosis (Isermann, 2006; Simani et al., 2013). The classical limit-value checking method is based on the first two supervision methods, that is, monitoring and automatic protection. This classical method has the advantage of simplicity and reliability, but it reacts only after a relatively large change. On the other side, the advanced methods of supervision and fault diagnosis can detect faults earlier. The advanced methods can be used in sensors and actuators fault diagnosis, closed-loop fault detection (FD) and process supervision in a transient state. Residual generation is the main stage in model-based FD. There exist many approaches for a residual generation. The three most common approaches: observer-based approach, parity equation approach and parameter estimation-based approach.

Several efforts handled the observer in control systems such as electrical drives (Doan et al., 2013; Ko, 1998; Nandam and Sen, 1988; Padmakumar et al., 2009; Ruderman and Iwasaki, 2014) and robotics (Heredia and Ollero, 2009; Weiss et al., 1987). The observer's design for control purposes should target estimating

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unmeasured states. In contrast, the observer's design for FD is used to estimate measured states (Isermann and Rolf, 2006). On the other side, observer-based FD has been conducted on many contributions (Ellis, 2002; Frank and Ding, 1997; Gadsden et al., 2013; Li and Yang, 2012; Liu and Collins, 2006; Luenberger, 1971; Vinodh et al., 2013; Yan and Edwards, 2008; Yi et al., 2014). Small autonomous helicopters sensor fault was detected using Observer/Kalman filter identification (Khalid. et al., 2011). In Yang et al. (1999), Kalman filter has been established to diagnose faults, whereas a hybrid genetic adaptive neuro-fuzzy inference system has been implemented for fault classification. A failure prediction method of preventing maintenance on a DC motor using state estimation through Kalman filtering has been introduced by Alkaya and Eker (2014). The sensor faults were detected using a Luenberger observer for DC motor by Tarantino et al. (2000) and BLDC motor by Eissa et al. (2015a,b). Generalized Luenberger observer-based FD was implemented by Vinodh Kumar and Jerome (2013). An unknown input observer (UIO) was implemented to detect sensor fault in a DC servo system (Sobhani and Poshtan, 2012). In Tan and Edwards (2002), a bank of UIOs was used to detect and isolate sensor and actuator faults in three-tank benchmark system. Successful sensor FD and reconstruction using sliding mode observers and application to a chemical process were introduced by Hakiki et al. (2006). The study by Yan et al. (2008) explored a robust sliding mode observer for the purpose of FD and diagnosis. Robust actuator FD and isolation for a class of nonlinear systems with uncertainty based on a sliding mode observer were considered by Chen and Saif (2007) and Ibaraki et al. (2005).

Currently, various research groups are developing algorithms addressing the observer FD problem. These can be classified into different categories based on their methodology (Chen and Saif, 2007); these include model-based approaches (Sobhani and Poshtan, 2012), artificial intelligent-based approaches (Eissa et al., 2015a,b) and optimization approaches. These methods are based on the state–space model in the observer's tuning and design. On the other side, there are methods don't use the full mathematical model, but need prior information about the system parameters. Form a practical view, the determination of an accurate mathematical model becomes difficult because of the complexity of the industrial engineering systems as well as the uncertainty in the measurements. Also, the system parameters are limited or unavailable for the most real industrial engineering applications. So, the main question is how to design an observer regardless of the mathematical representation of the industrial systems with unknown parameters.

This work proposes the observer's structure using the input–output measurements of the industrial system. In specific, the main contributions of this work are summarized in the following points:

I. Design and implement an observer's structure for FD purposes based on system measurements (Fig. 1).
II. Computes an inverse optimization problem in order to find an appropriate observer gain. Then, it performs an analysis of the minimum error in order to find these gains. This method also uses the offline Genetic Algorithm (GA) to solve the following optimization problem.
III. The practical application of the proposed observer to BLDC motor to detect the sensor faults, also compared with Luenberger observer.

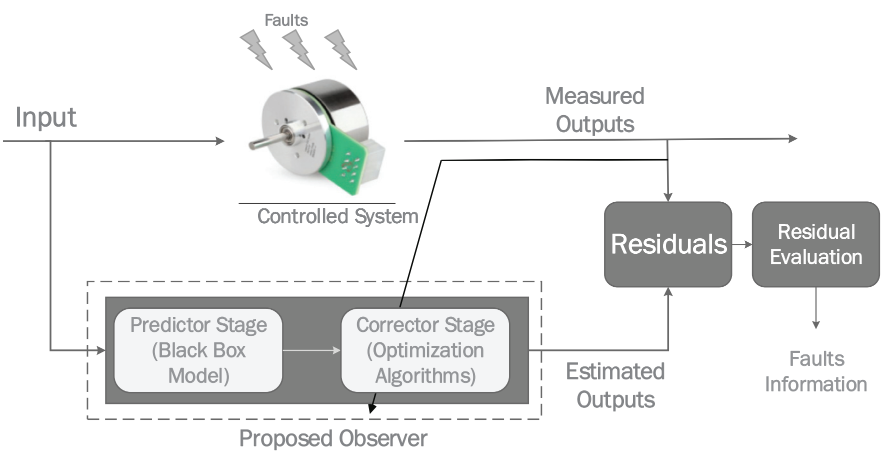

Fig. 1. Schematic diagram of the proposed observer-based FD approach.

The rest of this article is organized as follows: In Section 2, the proposed observer's design is presented. The experimental results of BLDC motor FD that are compared with Luenberger observer are presented in Section 3. Also, the comparison of results is illustrated. Conclusions are presented in Section 4, followed by the possible direction of future work.

2. Observer-Based FD Design

The observer-based approach is widely used in FD. The basic idea of the observer or filter-based technique is to estimate the states of the system from the measurement data. Therefore, compare the estimation states with the measurement states of the monitored system to generate the residual. The schematic diagram of this approach is shown in Fig. 2.

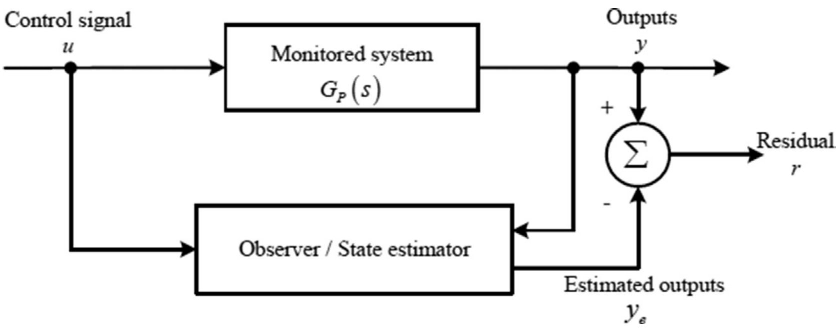

Fig. 2. Schematic diagram of an observer-based approach for residual generator.

2.1. Luenberger observer's design

The mathematical model of BLDC motor can be formulated in state–space representation as follows (Eissa et al., 2015a,b):

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

$$y(t) = C\ x(t) \tag{2}$$

where $x(t) \in R^{n\times 1}$ is a state vector, $u(t)$ represents control input vector, $y(t)$ is a measurement of the output vector and A, B and C are known as constant matrices.

The state vector, $x(t)$, has been selected such as:

$$x(t) = \begin{bmatrix} \theta \\ \omega \end{bmatrix} \tag{3}$$

where θ is the motor position and ω is the motor angular velocity.

The system input and output matrices for the model are:

$$A = \begin{bmatrix} -97.85 & -2.38e5 \\ 1 & 0 \end{bmatrix}, B = \begin{bmatrix} 1 \\ 0 \end{bmatrix}\ and\ C = [0 - 2.38e5] \tag{4}$$

Luenberger observer was designed to be used as a reference to judge the FD performance of the proposed observer. The procedures and mathematical analysis for the design of the Luenberger observer are the same as described (Fig. 3) (Eissa et al., 2015a,b).

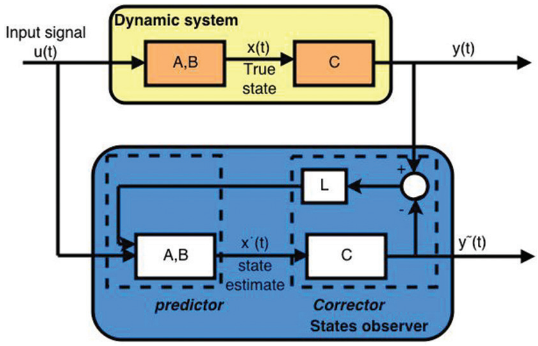

Fig. 3. The schematic diagram explains the Luenberger observer's structure.

The design of the classical Luenberger observer can be summarized as follows:
The structure of the Luenberger observer is described as:

$$\dot{\tilde{x}}(t) = A\,\tilde{x}(t) + B\,u(t) + L\left(y - C\,\tilde{x}(t)\right) \tag{5}$$

$$\dot{\tilde{y}}(t) = C\tilde{x}(t) \tag{6}$$

$\dot{\tilde{x}}(t) \in R^{n\times 1}$ represents the estimated state vector, $\dot{\tilde{y}}(t)$ is the estimated output and L is the observer's gain where the matrix L could be presented as:

$$L = \left[k_1;\ k_2\right] \tag{7}$$

By using the following formula:

$$G(s) = det\left(sI - \left(A - LC\right)\right) \tag{8}$$

The characteristic equation of the system is obtained Eq. (9):

$$s^2 + \left(978.5 + 2.4*10^5 k_2\right)s + \left(2.4*10^5 k_1 + 234.8*10^6 k_2 + 2.4*10^5\right) = 0 \tag{9}$$

The desired characteristic equation could be expressed as follows:

$$s^2 + 2\xi\omega_0 s + \omega_0^2 = 0 \tag{10}$$

where ω_0 is resonant frequency and ξ is damping factor.
By comparing Eq. (9) with Eq. (10), observer's gain equations could be obtained as follows:

$$k_2 = \left(8.4*10^{(-6)}*\xi*\omega_0\right) - 4*10^{-3} \tag{11}$$

$$k_1 = \left(4.2*10^{-6}*\omega_0^2\right) - 978.5*k_2 - 1 \tag{12}$$

2.2. The proposed observer's designs

In this article, we use the input–output systems based on deterministic dynamics, as shown in Fig. 4. This deterministic approach assumes that the input–output time series arises where $u(t)$ is a scalar input measurement and $x(t)$ is a scalar measurement output. It is then natural to attempt to forecast the behaviour of the input–output system in the following form.

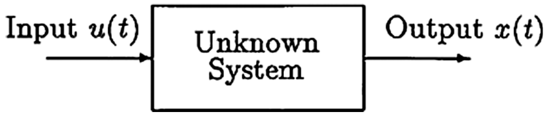

Fig. 4. Schematic diagram of a single input single output system.

$$x(t) = P(x(t - ts), x(t - 2\ ts), \ldots, x(t - M\ ts), u(t), u(t - ts), \ldots, u(t - (L-1)ts)), \tag{13}$$

where p is a function fitted to the input–output time series data and L and M are the lengths of input–output measurements time series (Casdagli, 1992).

The proposed observer comprises two main stages: the predictor stage and the correction stage, as shown in Fig. 1 (Poor, 2013; Szabat and Serkies, 2009). The structure of the proposed observer's scheme illustrated in Fig. 5. y is the measured output of the system and $\hat{y}$ is estimated output by the observer. Based on Fig. 4, the new formula of the proposed observer is described as:

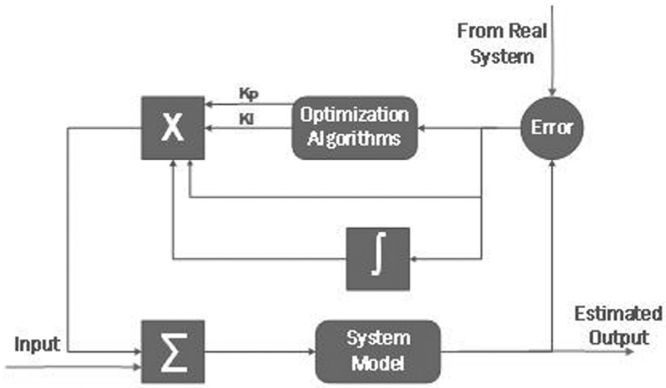

Fig. 5. Schematic diagram of the proposed observer's structure.

$$\hat{y} = (u + (k_p(y - \hat{y}) + k_i * \int (y - \hat{y})dt)) * p \tag{14}$$

where the u is the control input signal and k_p and k_i are the proportional and integral observer gains, respectively.

The optimization techniques (GA) used to determine the observer's gains. The main objective of the proposed algorithm is to determine the best observer's gains that are less sensitive to model uncertainty, disturbances, at the same time, more sensitive to the faults. The fitness function that has been used is defined in Eq. (15), where $e(t)$ is the estimation error.

$$\text{Fitness} = \sum e^2 \tag{15}$$

The proposed observer's design steps are as follows:

Step 1: Collect the input–output measurements of the system using the target sensor.
Step 2: Formulate the measurements to express as *p* term using Eq. (13).
Step 3: Put the initial range of optimization techniques.
Step 4: Run the offline optimization algorithm (GA) to find optimal observer gains according to the fitness function.
Step 5: Determine the optimal observer gains and test the gain under the normal and faulty cases.
Step 6: Repeat steps from 3 to 5 with another initial range until satisfactory results are reached.
Step 7: Determine the estimated value of the system output using Eq. (14).

3. Experimental Results and Discussion

In order to test the proposed approach described, a series of experiments were conducted through the experimental setup, as shown in Fig. 6. The setup comprises five main parts, namely BLDC motor with three hall effect sensors that are used for speed measurements, servo controller to drive the motor, a data acquisition card (DAQ), power supply and computer where MATLAB/Simulink program package was installed to perform the FD algorithms.

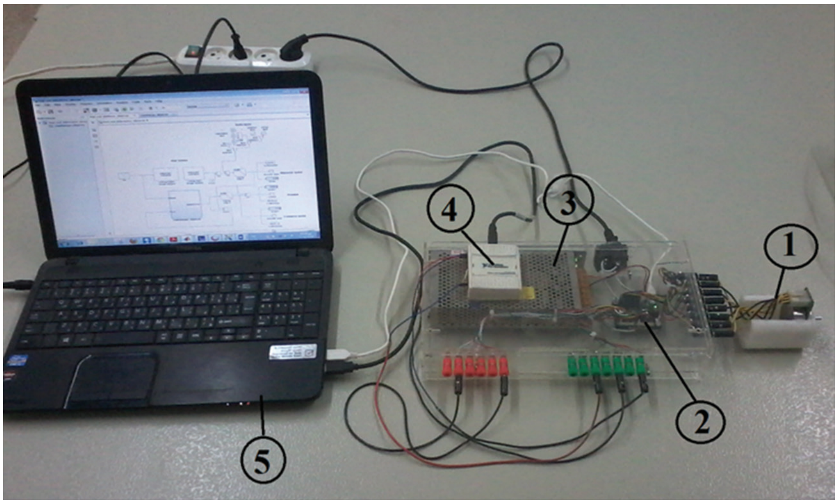

Fig. 6. The experimental setup: BLDC motor (1), a servo controller (ESCON 36/3 EC) (2), power supply (220V, 6A) (3), DAQ (NI-USB 6008) (4) and computer (5).

Several experiments were performed with 3 V of the input voltage and a sampling time of Ts = 5 ms to test the performance of observers. In this section, five cases of the experimental results will be presented in a subsequent order. The first case of the normal (non-faulty) case and another four cases will express the faulty case. The most common types of sensor faults were applied to the speed sensor of the BLDC motor (the fault created method present in (Eissa et al., 2015a,b).

In the normal case (non-faulty), Fig. 7 illustrates the measured and estimated speed and residuals signals of the proposed observer and the Luenberger observer. It should be remarked that the estimated error of the proposed

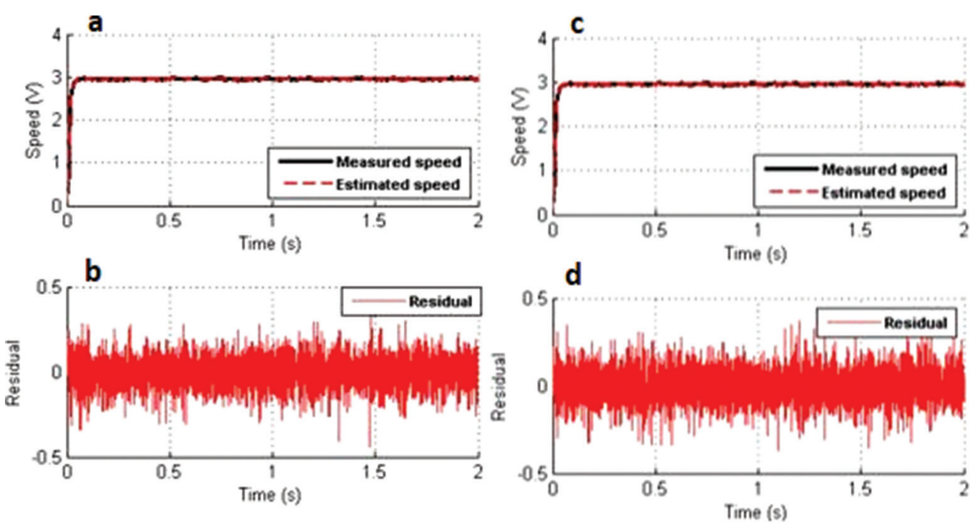

Fig. 7. Normal case: (a) measured speed and estimated speed, (b) residual by the proposed observer, (c) real speed and estimated speed and (d) residual by Luenberger observer.

observer case is less than that of the Luenberger observer's case. Also, the results show that the two observers give a satisfactory performance in the transient region.

The measured speed and its estimated value by the proposed observer and the residual signal at the abrupt fault case are shown in Figs. 8a and 8b, and the same results for the Luenberger are presented in Figs. 8c and 8d.

For the incipient fault case, Fig. 9 displays the measured and estimated speed and residuals signals when the intermittent fault applied for both observers. The results show that the proposed observer is able to detect the incipient fault clearly and with minimal estimation error compared to the classical observer.

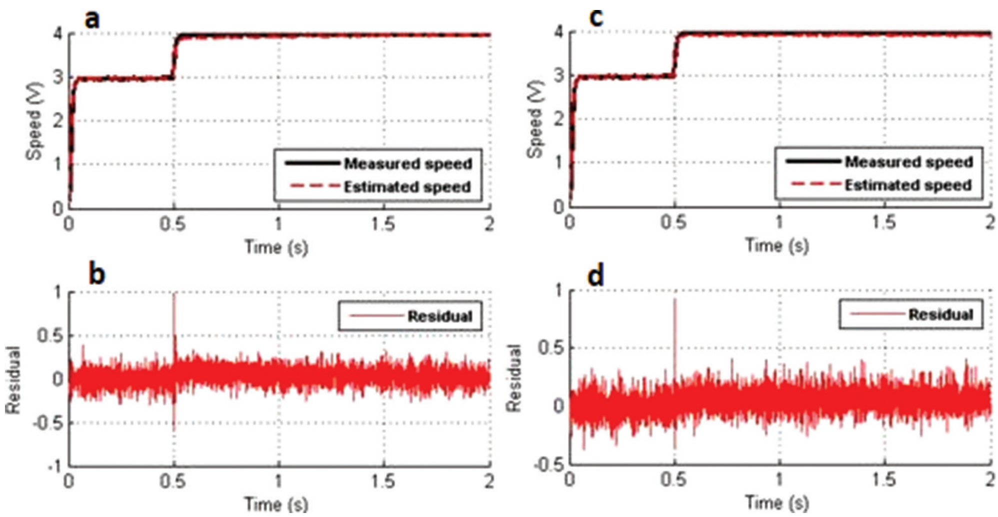

Fig. 8. Abrupt fault case: (a) measured speed and estimated speed, (b) residual by the proposed observer, (c) real speed and estimated speed and (d) residual by Luenberger observer.

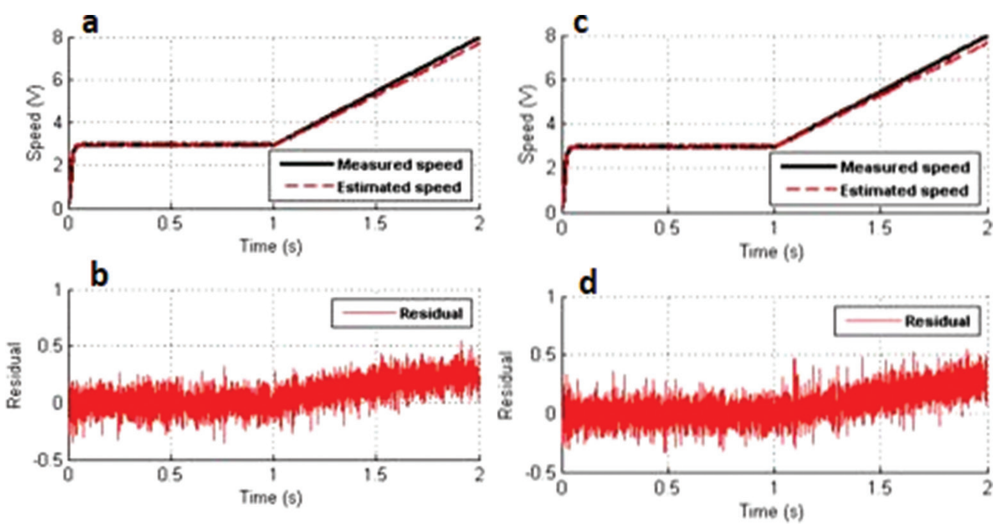

Fig. 9. Incipient fault case: (a) measured speed and estimated speed, (b) residual by the proposed observer, (c) real speed and estimated speed and (d) residual by Luenberger observer.

For the intermittent fault case, Fig. 10 shows the measured and estimated speed and residuals signals when the intermittent fault applied for both observers. The intermittent fault was successfully detected by the proposed observer.

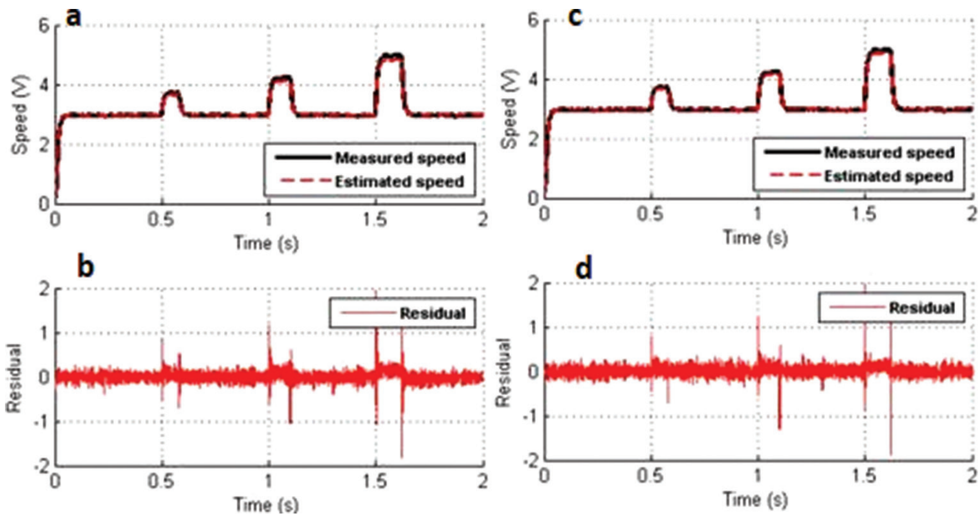

Fig. 10. Intermittent fault case: (a) measured speed and estimated speed, (b) residual by the proposed observer, (c) real speed and estimated speed and (d) residual by Luenberger observer.

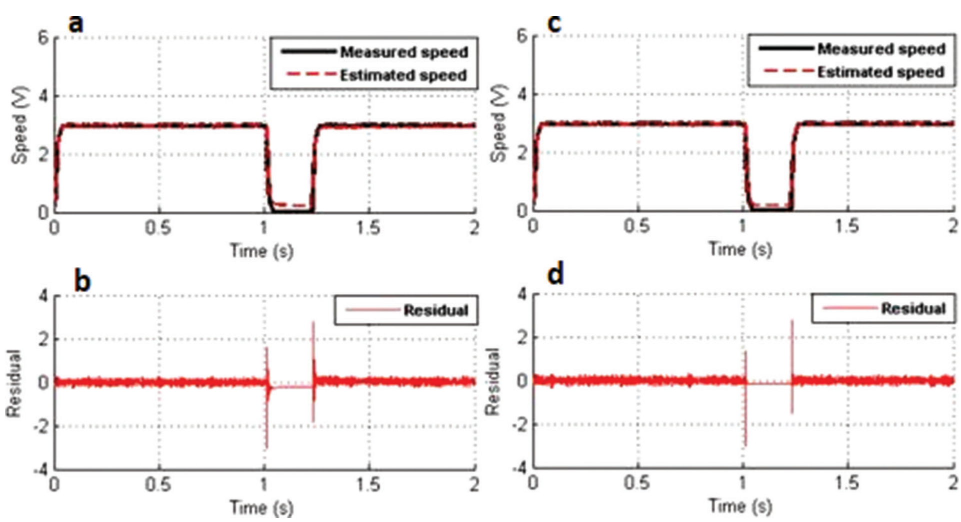

Fig. 11. Sensor failure case: (a) measured speed and estimated speed, (b) residual by the proposed observer, (c) real speed and estimated speed and (d) residual by Luenberger observer.

For the sensor failure case, Fig. 11 shows the measured and estimated speed and residuals signals when the intermittent fault applied for both observers. The proposed observer was able to detect this fault.

Overall, it is important to distinguish between the use of the observer for the control and FD purposes. On the one hand, the observer used to estimate the unknown states in the control systems. In contrast, the FD-based observer used to estimate the measurable states (i.e. motor speed). Added to this, the estimated states should follow real measurements [as shown in Eq. (14)]. Thus, the main role of the observer is detecting the peaks of the start and end of the fault period and ignored the noises and the system parameters disturbances (as shown in Figs. 7–11). Alternatively, any change result from other sources (noise, disturbers) will be considered as a fault, and the false fault alarm will be increased (Alkaya and Eker, 2014; Eissa et al., 2015a,b; Isermann, 2006)

Four faults have been detected using the proposed observer, namely abrupt fault, incipient fault, intermittent fault and the sensor faultier fault. In normal cases, the proposed observer's estimation error has been compared with the classical Luenberger, as shown in Table 1. The estimation errors were calculated using the following equation (Szabat et al., 2015):

Table 1. Observer's estimation errors

Average estimation error (e) (normal and faulty cases)	Proposed observer	Luenberger observer
e	0.0707	0.0727

$$\Delta_v = \frac{\sum_{i=1}^{N} |v - ve|}{N} \tag{15}$$

where N is the total number of samples, v is the real variable and ve is the estimated variable.

The results show that the estimated error of the proposed observer is less than the estimated error of the traditional observers. Finally, all experimental results are presented in this article; in addition, the results that were published in (Alkaya and Eker, 2014; Tarantino et al., 2000) have advocated that the proposed observer's work is a good estimator for FD purposes.

4. Conclusion

Sensor faults of BLDC motor have been detected based on a new observer's design. In this work, an experimental study on BLDC motor is presented. Also, classical Luenberger observers rather than the proposed observer design are camper the effectiveness of the proposed observer for FD purpose by comparing their performances in faults detection. Based on the comparison of the experimental results, the proposed back box observer provides the advantage over the traditional one. Part of the future work implement fuzzy logic to develop the gain tuning method to be adaptive.

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