

Multi-sensor Fault Detection and Isolation for EMB SystemBased on Unknown Input Observer

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ABSTRACT: Electro-mechanical brake (EMB) systems generate the braking force with electric motors and use several sensors for feedback control. This paper presents a model-based sensor fault diagnostic approach that employs an Unknown Input Observer (UIO) technique to classify sensors as being healthy or unhealthy and even simultaneously occurred faults in two different sensors. The proposed scheme is organized by UIO logic and a decision-making unit. UIO logic estimates sensor values using the inputs and outputs of EMB system and a decision-making unit identifies the faulty sensor based on a deterministic rule and the estimated ones from UIO logic. Unlike other model-based fault detection and isolation schemes, the proposed one needs only one UIO instead of a bank of observers and UIOI is sufficient for detecting and isolating faults simultaneously occurred. Simulation results are presented to verify the effectiveness of this proposed diagnostic approach.

KEYWORDS: electro-mechanical brake (EMB) system, unknown input observer, fault detection and diagnosis, sensor fault, simultaneous faults

I. INTRODUCTION

According to the increasing need for safety and convenience in the automotive industry, various electronic parts and related techniques have been introduced to replace conventional mechanical parts. These new parts provide benefits of faster response time, higher fuel efficiency, eco-friendly characteristics, and so on [1, 2]. Despite the advantages of these systems, electric power-assisted brake systems are still under development and have not been widely commercialized yet because of safety-critical features of the braking system [3]. The electro-mechanical brake (EMB) system uses an electric motor to generate the proper braking force according to data from the brake pedal sensor. This system consists of an EMB controller, an electric motor, speed reduction unit, linear motion converter, calliper, and brake pad, and sensors. These sensors provide feedback data to the EMB controller and certain sensors are especially safety-critical components; their failure might decrease the braking performance and even cause a traffic accident. Therefore, sensor faults in EMB systems should be detected and diagnosed accurately and rapidly to guarantee the reliability of the system [4]. Fault detection and isolation (FDI) (or fault detection and diagnosis) schemes monitor measurable variables in systems, detect unusual symptoms and classify them according to what they are and where and when they happen. The model-based fault detection method estimates the system variables using a mathematical model of the system. Unlike hardware redundancy methods, which use redundant components, model-based methods replace the additional hardware with software; this saves additional cost and space [5-7]. Based on the measured input and output signals, the model-based detection methods generate the estimated outputs and residuals. A residual is the difference between the measured output from a real system and the estimated output from a system model and it is used to judge the state of the system as faulty or not and to identify the location and the type of the fault in FDI.

In this paper we suggest a multi-sensor FDI scheme that can detect and isolate simultaneously occurring sensor faults using the unknown input observer. The whole process of the multi-sensor FDI scheme using UIO is shown in Fig. 1.

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The UIO is built using a mathematical model of the system; this model predicts the system outputs $\hat{y}(t)$, based on the inputs as the system input $u(t)$, and the measured outputs, $y(t)$. Then, the residuals $r(t)$ are generated; these are the difference between $y(t)$ and $\hat{y}(t)$. Finally, based on the residuals and the predefined threshold values, the decision making logic produces the fault detection results as fault alarms.

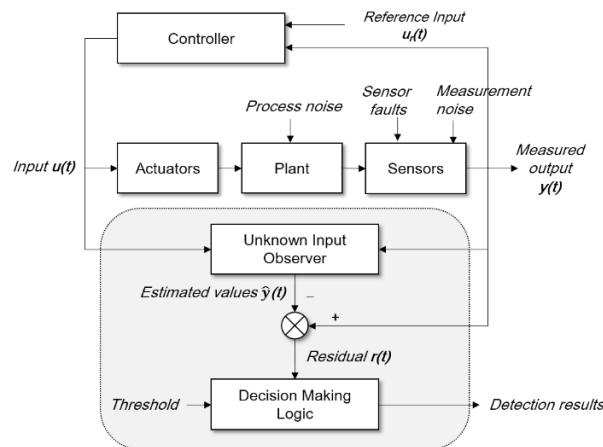


Fig. 1. Schematic diagram of multi-sensor fault detection and isolation with UIO for EMB system

II. RELATED WORK

There have been several previous studies on model-based FDI methods for the detection of sensor faults in EMB systems. In [8-10], Hwang et al. suggested a sensor fault diagnosis method that combines parity space and observer design approaches for EMB sensors. For electrical motors in different fields, an observer or Kalman filter is generally used to diagnose sensor faults. Current sensor fault detection and isolation using an observer scheme for a doubly fed induction generator is studied in [11]; an extended Kalman filter algorithm is adopted for a current, speed, and voltage sensor FDI in an interior permanent magnet synchronous motor drive in [12]. An unknown input observer is designed to detect three different sensor fault scenarios in a wind turbine in [13]. However, all of these past works have included the assumption that only one sensor fault will occur at a time; also, previous works have tried to detect and isolate single sensor faults simultaneously.

III. EMB SYSTEM AND ITS MODEL

The EMB system is composed of the EMB controller, actuators, and sensors. The working principle of the EMB is as follows: when a driver presses the brake pedal, the main engine control unit (ECU) calculates the required braking force as per driver demand; the main ECU transmits the control signal to the EMB ECU to generate braking force. The motor driver in the EMB ECU rotates the motor, and the rotational motion of the motor is transformed into a linear motion of the head through the planetary-type reduction gear and the screw-thread gear. The linear motion of the head generates a clamping force between the pad and the disk, which provides the braking torque. The three kinds of sensors are motor current sensors, motor speed sensors, and clamping force sensors. Each sensor provides measured data to the EMB controller in real-time. In this paper, the clamping force sensor is replaced by the clamping force estimator, which uses a speed sensor and is from [14] and in Fig.2.

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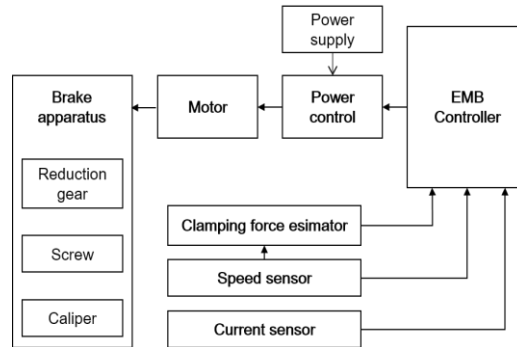


Fig.2. Schematic diagram of EMB system with motor speed, current sensors and clamping force estimator

First, the motor is modelled using the standard equations for a permanent-magnet DC motor, e.g.,

$$\frac{di}{dt} = \frac{1}{L} (V - Ri - K_{emf} w) \quad (1)$$

where i , L , and R are the armature current, the armature inductance, the armature voltage, and the armature resistance, respectively. K_{emf} is the back electromotive force voltage and w is the motor rotational velocity. The electrical torque of the motor and the torque balance equation for the mechanical components can be represented as,

$$\frac{dw}{dt} = \frac{1}{J} (T_m - T_f - T_l) \quad (2)$$

where T_m , T_f , T_l , and J are the motor torque, the resistance torque, the load torque, and the angular inertia of the motor, respectively. Assuming that the field current is constant, the motor torque can be expressed as,

$$T_m = K_m i \quad (3)$$

where K_m is the motor torque constant. The resistance torque is mainly composed of viscous friction torque in the ball screw,

$$T_f = B_f w. \quad (4)$$

The load torque is directly related to the clamping force between the rotor and the brake pad,

$$T_l = \left(\frac{P_s}{2\pi\eta} \right) f_{cl} \quad (5)$$

where B_f is the damping coefficient and P_s , η , and f_{cl} are the screw pitch, screw efficiency, and clamping force, respectively [15]. In a low-speed case, the estimated clamping force will be nearly linearly proportional to the motor angle, θ [16]. In order to construct a linearized and simplified mathematical model of the EMB system, the following equation is adapted,

$$\frac{df_{cl}}{dt} = K_\theta \frac{d\theta}{dt} = K_\theta w \quad (6)$$

where K_θ is the proportional constant.

The above equations are expressed in a state space model of an EMB system as,

$$\begin{aligned} \frac{d}{dt} \begin{bmatrix} i \\ w \\ f_{cl} \end{bmatrix} &= Q \begin{bmatrix} i \\ w \\ f_{cl} \end{bmatrix} + \begin{bmatrix} 1/L \\ 0 \\ 0 \end{bmatrix} V \\ \begin{bmatrix} i \\ w \\ f_{cl} \end{bmatrix} &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} i \\ w \\ f_{cl} \end{bmatrix} \end{aligned} \quad (7)$$

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$$\text{where } Q = \begin{bmatrix} R/L & -K_{emf}/L & 0 \\ K_m/J & -B_f/J & -P_s/2\pi\eta J \\ 0 & K_\theta & 0 \end{bmatrix}$$

IV. FAULT DIAGNOSIS AND ISOLATION DESIGN

1. Design of the Unknown Input Observer

Consider a continuous linear time invariant system model with disturbances described as below, [17]

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + Ed(t) \\ y(t) &= Cx(t) \end{aligned} \quad (8)$$

where $x(t)$, $y(t)$, $u(t)$, and $d(t)$ are the state vector, output vector, input vector, and an unknown scalar function representing the disturbance, respectively. Matrices A, B, C, and E correspond to the system coefficient matrix, input coefficient matrix, output coefficient matrix, and the unknown input disturbance matrix, respectively.

And the structure of the unknown input observer is taken from [18]

$$\begin{aligned} \dot{z}(t) &= Fz(t) + TBu(t) + Ky(t) \\ \hat{x}(t) &= z(t) + Hy(t) \end{aligned} \quad (9)$$

where $\hat{x}(t)$ is the estimated state vector, and $z(t)$ is the state of this observer, and the observer state-space matrices F , T , K , and H will be designed to decouple the disturbances from the state estimation error, $e(t)$.

$$\begin{aligned} e(t) &= x(t) - \hat{x}(t) = x(t) - z(t) - Hy(t) \\ &= x(t) - x(t) - HCx(t) \\ &= (I - HC)x(t) - z(t) \end{aligned} \quad (10)$$

The derivative of the error vector can be written as,

$$\begin{aligned} \dot{e}(t) &= (A - HCA - K_1C)e(t) \\ &\quad + [F - (A - HCA - K_1C)]z(t) \\ &\quad + [K_2 - (A - HCA - K_1C)H]y(t) \\ &\quad + [T - (I - HC)]Bu(t) + (HC \\ &\quad - I)Ed(t) \end{aligned} \quad (11)$$

where $K = K_1 + K_2$.

If the state estimation error vector, $e(t)$ comes close to zero asymptotically, regardless of the presence of the disturbance (the unknown inputs) in the system, the UIO is defined.

To synchronize UIO, the following relations have to hold true:

$$\begin{aligned} (I - HC)E &= 0 \\ T &= I - HC \\ F &= A - HCA - K_1C \\ K_2 &= FH \end{aligned} \quad (12)$$

Given these relationships, the derivative of the state estimation error reduces to $\dot{e}(t) = Fe(t)$. By selecting a stage F as a Hurwitz matrix, $e(t)$ will be made to approach zero asymptotically and then $\hat{x}(t)$ converges to $x(t)$.

Necessary and sufficient conditions to be a UIO for defined system in equation. (7) are taken from [19]:

(i) $\text{rank}(CE) = \text{rank}(E)$

(ii) (C, A_1) is a detectable pair,

where $A_1 = A - E[(CE)^TCE]^{-1}(CE)^TCA$

The system in equation (1) is modified as,

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + Ed(t) \\ y(t) &= Cx(t) + f_s(t) \end{aligned} \quad (13)$$

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where $f_s(t)$ is an immeasurable vector considered as an additive that biases the sensor fault; it is reflected in Equation (7) as additive signals to current, speed, and clamping force sensors.

$$\begin{bmatrix} i \\ w \\ F_{cl} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} i \\ w \\ F_{cl} \end{bmatrix} + \begin{bmatrix} f_1 \\ f_2 \\ f_3 \end{bmatrix}$$

where the measured output is expressed as a sum of true values of i, w_m, F_{cl} , and the sensor fault signals of f_1, f_2, f_3 , respectively.

The residual $r(t)$ is a generated signal based on the input $u(t)$ and output $y(t)$; commonly, the difference between the measured output $y(t)$ and an estimated output $\hat{y}(t)$ can be computed based on the system's model, as follows,

$$\begin{aligned} r(t) &= y(t) - \hat{y}(t) = y(t) - C\hat{x}(t) \\ &= (I - CH)y(t) - Cz(t) \end{aligned} \quad (14)$$

Fig.3 shows the residual generation part using UIO, this part organizes one primary UIO and two secondary UIOs and the number of secondary UIOs is the same as the number of sensors in the system. Residual r_i is the difference between the output of the secondary UIOs and the measured output $y_i(t)$; each of these values is multiplied by matrix C_i before comparison. Matrix C_i is derived when the i_{th} sensor is removed from the C matrix in Equation (7). Then secondary UIOs are constructed as:

$$\begin{aligned} \dot{z}_i(t) &= F_i z_i(t) + T_i B u(t) + K_i y_i(t) \\ r_i(t) &= (I - C_i H_i) y_i(t) - C_i z_i(t) \end{aligned} \quad (15)$$

The matrices F_i, T_i, K_i , and H_i are found in the following conditions, which have to be satisfied to design UIOs:

$$\begin{aligned} H_i C_i E &= E \\ T_i &= I - H_i C_i \\ F_i &= T_i A - K_{i1} C_i \\ K_{i2} &= F_i H_i \\ K_i &= K_{i1} + K_{i2} \end{aligned} \quad (16)$$

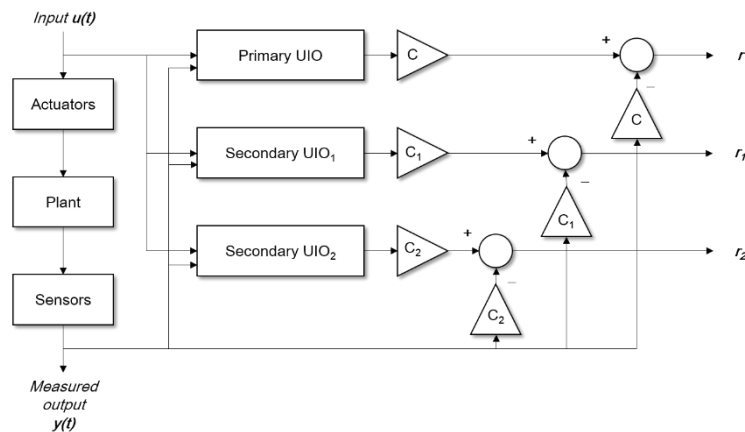


Fig.3. Block diagram of residual generation part for sensor fault diagnosis and isolation using Unknown Input Observer

2. Design of Decision-making unit

In the Decision-making unit, the generated residuals are entered as the inputs; these are the primary residual and the secondary residuals. The primary residual with two different sensors is defined as,

$$r_p(t) = [r_p^1 r_p^2]^T$$

And, these secondary residuals, with three different sensors, are defined as,

$$r_{si}(t) = [r_{si}^1 r_{si}^2]^T$$

$$\text{for } 1 \leq i \leq 2 \text{ and } r_{si}^j = 0 \text{ for } i = j$$

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Each secondary residual generator is driven by all inputs and all outputs, except for one output.

The multi-sensor fault decision process is a simple comparison test with predefined thresholds. A sensor fault is presented at the i_{th} sensor if

$$Fault\ Detection_i = \begin{cases} 1 & \text{if } (|r_p^i| > THR_i) \& (|r_{sk}^i| < THR_i) \\ 0 & \text{else} \end{cases}$$

$$for\ k = \begin{cases} 1 & \text{if } i = 2 \\ 2 & \text{if } i = 1 \end{cases}, for\ 1 \leq i \leq 2$$

where THR_i is the threshold for the i_{th} sensor. If $Fault\ Detection_i$ is zero, there is no fault in the i_{th} sensor; if $Fault\ Detection_i$ is one, this means that a fault is detected in the i_{th} sensor. Each threshold for each sensor is determined through various test results using the simulated data, such that false detections are avoided when the sensor fault is still detected.

V. SIMULATION RESULTS

To evaluate the proposed approach, the simulation environments are set up. Through experiments intended to mimic a faulty situation, monitor sensors detect and isolate faulty sensors in the EMB system. The reference input of the EMB controller is the clamping force; the EMB system is implemented based on Equation (7). In the fault injection logic, the faulty signals are added to the outputs of the EMB system, which means the measured sensor values and the UIO logic generate residuals and, based on the produced residuals, the decision making logic detects and diagnoses the sensor fault and generates fault detection signals for each of the sensors. The EMB system parameters for the simulation are given in Table 1; reference clamping force input is a step input that starts at 10KN and reaches 20KN after 1 second as in Fig. 4 (a).

Table 1. EMB system parameters for simulations

Category	Parameters	Description	Values
EMB Motor	R_a	armature resistance	1.5
	L_a	armature inductance	3.6e-3
	J_m	motor angular inertia	4e-4
	K_{emf}	back-electromotive force voltage	12e-3
	K_m	motor torque constant	0.37
EMB apparatus	B_f	damping coefficient	0.005
	P_s	screw pitch	0.05
	η	screw efficiency	0.5
	K_{th}	proportional constant	8e4

1. Without any sensor faults

Fig.4 shows the simulation results in normal conditions; no sensor faults. Fig. 4(b) shows the clamping force estimator output using motor speed, (c) represents motor current sensor output, (d) shows the motor speed sensor output. The three residuals, R_p , R_{S1} , and R_{S2} from the UIO are shown in (e), (f), (g) respectively and the fault detection outputs for motor current sensor (h) and motor speed sensor (i) are derived from them.

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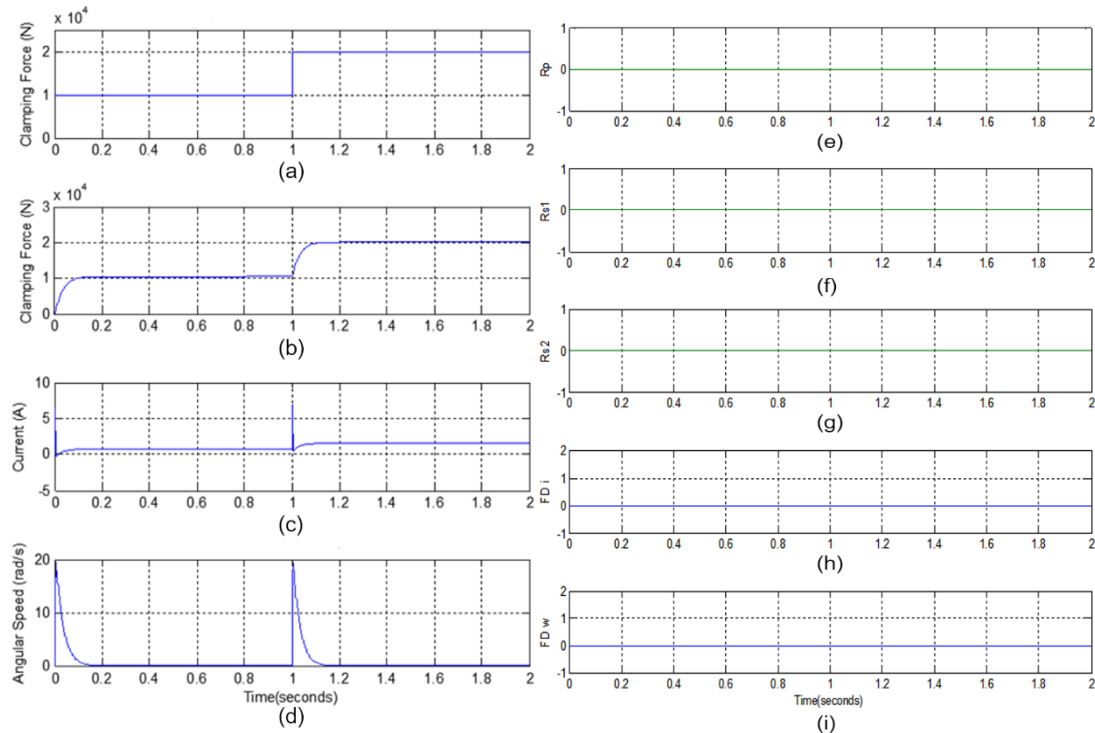


Fig. 4. Simulation results of EMB system without any sensor faults: (a) the reference clamping force (b) the clamping force estimator output (c) the motor current sensor output (d) the motor speed sensor output (e) primary residual (f) secondary residual1 (g) secondary residual2 (h) fault detection result for current sensor (i) fault detection result for speed sensor

2. With current and speed sensor faults

In this simulation, the current sensor fault, 1.5A from 0.6s to 1.2s, and the speed sensor fault, 3rad/s from 0.8s to 1.4s, overlap each other from 0.8s to 1.2s. In Fig.5(b) the clamping force estimator output can't follow the reference clamping force in Fig 5(a); the reasons can be found in the clamping force estimator and EMB controller. First, because we adopt a clamping force estimator using the motor speed data, the motor speed sensor fault makes wrong clamping force estimation. Second, the EMB controller in this simulation uses a cascaded proportional-integral (PI) control scheme, which organizes three cascaded PI control loops. The outside loop (or master loop or primary loop) controls the clamping force; the two inner loops (or slave loop or secondary loop) control the motor speed and the current, respectively. Generally, the cascade control scheme involves one or more feedback control loops that use measurement signals to control one primary variable. The output of the primary controller determines the set point for the secondary controller; the output of the secondary controller is used to adjust the control variable. In this case, by the speed sensor fault, the estimated clamping force is incorrect and the master loop fails to produce the proper set point. The three residuals, R_p , R_{s1} , and R_{s2} from the UIO are shown in Fig.(e), (f), (g) respectively and the fault detection for currents is shown in Fig.5(h) and it shows current sensor fault is occurred from 0.6s to 1.2s. And Fig. 5(i) represents the fault detection for speed sensor and it depicts that speed sensor fault arises from 0.8s to 1.4s. This result indicate that our scheme can detect not only a single sensor fault, but also two overlapping sensor faults.

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Vol. 4, Issue 12, December 2015

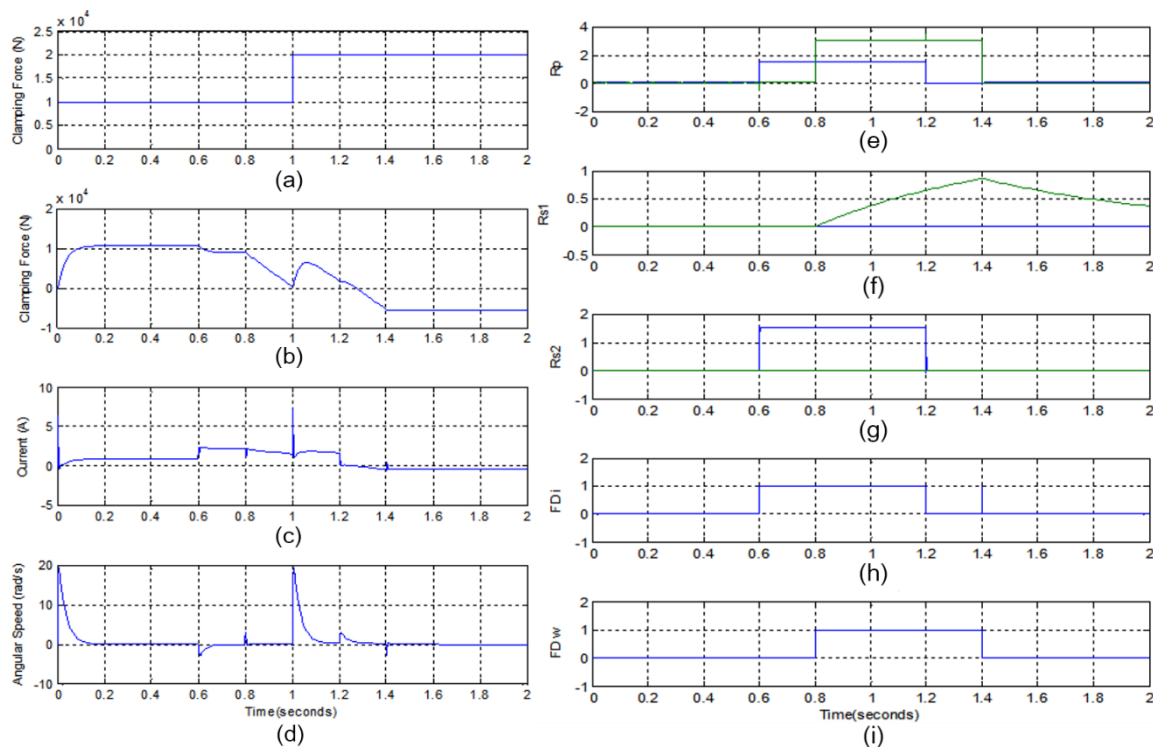


Fig. 5 Simulation results of EMB system with the motor current fault from 0.6s to 1.2 and motor speed sensor fault from 0.8s to 1.4s (a) the reference clamping force (b) the clamping force estimator output (c) the motor current sensor output (d) the motor speed sensor output (e) primary residual (f) secondary residual1 (g) secondary residual2 (h) fault detection result for current sensor (i) fault detection result for speed sensor

VI. CONCLUSION

In this paper we first introduce the architecture and mathematical model of our EMB system and suggest a multi-sensor fault detection and isolation scheme based on them. Our EMB system has motor current and motor speed sensors; the clamping force sensor is superseded by the clamping force estimator, which uses the motor speed. The simple mathematical model is used to establish the unknown input observer structure; this UIO estimates the EMB system outputs and then generates the residuals, the differences between the residuals, and the measured sensor output from the EMB system. Using each of the residuals and the predefined thresholds of each sensor, sensor faults are well detected even when two sensor faults simultaneously occur. We demonstrate the EMB system and the multi-sensor fault detection and isolation algorithm; the simulation results prove the efficiency of our suggested system. And, as we know from the simulation results, to diagnose sensor faults and report abnormal conditions are not a sufficient and ultimate goal. Next, we will study multi-sensor fault-tolerant control schemes that can detect and isolate simultaneously arising faults in two or more sensors, as well as guarantee the sustainable control of the system.

ACKNOWLEDGMENT

This work was supported by the DGIST R&D Program of the Ministry of Science, ICT and Future Planning of Korea (15-RS-03).

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