Design and Evaluation of Model-Based Health Monitoring Scheme for Automated Manual Transmission

Health monitoring of automated manual transmission (AMT) in modern vehicles can play a critical role to avoid its malfunctions and ensure vehicle functional safety. In order to meet this demand, this paper presents a model-based fault detection and identification (FDI) scheme for AMT. After developing the fault model of AMT, structural analysis (SA)-based fault detectability and isolability is realized with the available set of sensors, prior to design and development of residuals. The residuals are generated by employing the theory of SA, where the concepts of analytical redundant relationship (ARR) are utilized to make residuals stable and robust. Finally, the proposed FDI scheme is successfully evaluated to detect and isolate the sensor faults in EcoCAR2 AMT.

Keywords: model-based fault detection and identification, residual design, structural analysis, automated manual transmission

1 Introduction

An AMT employs a transmission control unit (TCU) and hydraulic/electric actuators to engage/disengage clutch and to shift gears swiftly. AMT is widely used in commercial trucks and passenger cars due to its lightweight, high fuel efficiency, and low manufacturing cost.

The gear shifting in AMT is highly dependent on a set of sensors sending feedback to the TCU. These sensors can malfunction due to sudden shocks, severe vibrations, and extreme temperatures [1]. These situations may force the sensor to send erroneous feedback to the TCU that can be the cause of inaccurate commands issued to the actuators. As a result, the actuators will not shift the synchronizer at the right time and in the correct position. Depending on the extent of the fault, gear shifting may not occur and the probability to damage components like synchronizer, gear, shaft, etc., becomes very high. If the shifting time is altered due to faults in the sensor, then the vehicle drivability will deteriorate. Finally, functional safety may also be compromised by incorrect shifting. This motivates the study of FDI for AMT sensors presented in this paper, in support of the automotive industry goal to produce ISO 26262 compliant vehicles [2].

Automotive transmission including automatic and AMTs fault diagnosis has been the focus of researchers in the last decade [3,4]. Cote and Speranza [5] provided a new and improved control method for AMT systems, which involves sensing and identifying a fault in the speed sensors and modifying the logic routines or algorithms by which the system is operated in tolerance of such sensed fault. Qin et al. [6] and Guihe et al. [7] outlined an analytical redundancy fault-diagnosis method of AMT to detect and diagnose the faults of the sensors, the actuators, and the unit assemblages. Yin et al. [8] employed software fault tolerant technique to improve the reliability of AMT and put forward three kinds of fault tolerant methods suitable for AMT control software, including software redundancy, software antdisturbance, and fault diagnosis and disposal for sensors and actuators. Liu et al. [9] established an online fault-diagnosis system for AMT based on controller area network bus and principal component analysis-subtractive clustering-adaptive-network-based fuzzy inference system model. Xi [10] utilized redundancy analysis method and action analysis method to detect the failures in the AMT and developed a fault diagnostic system of air-drive AMT in heavy commercial vehicle by model-based design. Xi et al. [11] also designed a fault-diagnosis device to debug AMT more quickly and accurately based on the ISO 15765 protocol, which adopts the flow control mechanism and has offline diagnostics function. Zhang et al. [12] proposed a comprehensive hazard analysis method based on functional model and applied it to AMT control system. Zhang et al. [13] designed a microcontroller-based AMT online diagnosis instrument, which can communicate with TCU real-time to get fault codes and data through controller area network bus and realize online diagnosis. Peng et al. [14] studied fault detection and diagnosis strategy based on AMT system trajectory and discussed fault diagnosability of AMT hybrid system based on AMT system’s fault model and fault threshold function. Teng et al. [15] developed a diagnostic strategy of logic redundancy for fault diagnosis of an AMT and verified it in a simulation model-based on MATLAB/SIMULINK and LAVIEW softwares. Li and Zhang [16] presented a comprehensive software hazard analysis method applied to AMT and integrated preliminary hazard analysis, fault tree analysis (FTA), and failure mode and effect analysis (FMEA) for investigating potential software causes of system
hazards. Zhong et al. [17] listed several failure modes and extreme conditions of AMT and simulated some of them in MATLAB/Simulink to optimize AMT actuator and control strategy when AMT is failed or vehicle is driven in extreme conditions.

The existing literature on fault diagnosis of AMT shows techniques that rely on a large number of sensors and plenty of data to detect and isolate the faults “data-based”, so the work of setting up and validating the FDI scheme is complicated and tedious. To make the FDI scheme efficient and economic, this work focuses on system level FDI by employing the concept of model-based SA. A first and necessary step to the FDI scheme is careful and detailed fault modeling of the AMT [16–18]. Following a brief review of these results, the paper outlines the detailed process of executing SA, including fault detectability and isolability analysis, and sequential residual design. Finally, the FDI scheme is shown to be efficient and effective by experimental validation.

The paper is organized as follows: The AMT structure is reviewed, and the available sensors installed in it are listed in Sec. 2. Fault modeling is discussed in Sec. 3. SA for AMT is performed in Sec. 4 to analyze which sensor fault can be detected and isolated. Residual generators are designed utilizing the concept of SA in Sec. 5. Section 6 shows the simulation and validation of the proposed FDI scheme followed by the conclusion in Sec. 7.

2 AMT Review and Its Sensor Setting

The AMT discussed here is clutch free and made up of six-speed manual transmission and two linear shifting actuators, which is used in the EcoCAR2 plug-in hybrid electric vehicle (PHEV) vehicle in the Center for Automotive Research (CAR) of the Ohio State University [18].

2.1 AMT Structure Review. Figure 1 gives a sketch of the six-speed AMT structure [19], which is made up of two parts: one is the transmission box, and the other is the actuator(s). The transmission box is responsible for transforming the torque and velocity from the electric motor (EM) to the wheels when the vehicle works in the series mode; the two linear actuators in AMT have the same structure and are responsible for gear choosing (X position) and gear shifting (Y position), respectively.

2.2 Sensor Setting in the AMT. There are usually a set of sensors used in AMT for the purpose of acting as a feedback signals for control requirements as well as monitoring health status. The sensor setting in this paper is derived from the AMT used in EcoCAR2 PHEV.

To meet the requirements of control, there are eight sensors used in AMT detailed in Table 1. More information can be found in Ref. [20].

3 Fault Modeling of AMT

Fault modeling consists of a group of mathematic equations that expresses the physical mechanism of the AMT system. The following residual design will be based on fault modeling when applying the methodology of SA.

3.1 Actuators Model. From Fig. 2, we can see that actuator model is easily obtained by the combination of the DC model and mechanical model. The sole difference between the X and Y actuator is that X actuator uses one more angular displacement sensor (ST1) to confirm the gear shifting position.

(1) X actuator
Equation (1) \((e_1 - e_3)\) is the fault model for X actuator, where \(e_1 - e_3\) are the system model, and \(e_6 - e_8\) are the sensor model

\[
\begin{align*}
e_1: & \quad L_{i_1} \frac{di_{i_1}(t)}{dt} = e_{i_1}(t) - R_s i_{i_1} - e_{b_1}(t) \\
e_2: & \quad e_{b_1}(t) = K_{b_1} i_{a_1} \frac{dS_1(t)}{dt} \\
e_3: & \quad T_{i_1}(t) = K_{i_1} i_{a_1} \\
e_4: & \quad J_{i_1} \frac{d^2S_1(t)}{dt^2} = T_{i_1}(t) - T_L - B_{i_1} \frac{dS_1(t)}{dt} \quad (1) \\
e_5: & \quad S_{T_1}(t) = K_{T_1} S_{i_1}(t) \\
e_6: & \quad y_{a_1}(t) = i_{a_1}(t) + f_{a_1} \\
e_7: & \quad y_{S_1}(t) = S_1(t) + f_{S_1} \\
e_8: & \quad y_{ST_1}(t) = S_{T_1}(t) + f_{ST_1}
\end{align*}
\]

Here, the meaning of the variables in Eq. (1) can be found in Tables 5 and 6 of the Appendix.

(2) Y actuator
Equation (2) \((e_9 - e_{13})\) is the fault model for Y actuator, where \(e_9 - e_{13}\) are the system model, and \(e_{14} \) and \(e_{15}\) are the sensor model

Fig. 1 Sketch of the EcoCAR2 AMT

Fig. 2 Structure of the AMT linear actuator (X-direction)
transmission model, which is shown in the following equation

\[ e_9: L_{a2} \frac{di_{a2}(t)}{dt} = e_{a2}(t) - R_{a2} \cdot i_{a2}(t) - e_{b2}(t) \]

\[ e_{10}: e_{a2}(t) = K_{e2} \frac{dS_1(t)}{dt} \]

\[ e_{11}: T_{a2}(t) = K_{a2} i_{a2}(t) \]

\[ e_{12}: J_{a2} K_{e2} \frac{dS_1(t)}{dt} = T_{a2}(t) - T_{L2} - B_{a2} K_{e2} \frac{dS_1(t)}{dt} \]

\[ e_{13}: S_{f2}(t) = K_{f2} S_2(t) \]

\[ e_{14}: y_{SL}(t) = i_{a2}(t) + f_{ia} \]

\[ e_{15}: y_{S2}(t) = S_2(t) + f_{S2} \]  

(2)

Here, the meaning of the variables in Eq. (2) can be found in Tables 5 and 6 of the Appendix.

### 3.2 Transmission Model

Considering the quick verification for the methodology in this paper, we use a simplified model for transmission model, which is shown in the following equation (\( e_{16} - e_{20} \)):

\[ e_{16}: V_i(t) = K_a \cdot o_2(t) \]

\[ e_{17}: o_1(t) = o_2(t) \cdot G_R \cdot B_R \] (\( G_R \neq 0 \))

\[ e_{18}: y_{oa}(t) = o_1(t) + f_{oa} \]

\[ e_{19}: y_{oa2}(t) = o_2(t) + f_{oa2} \]

\[ e_{20}: y_{V_i}(t) = V_i(t) + f_{V_i} \]  

(3)

Here, the meaning of the variables in Eq. (3) can be found in Tables 5 and 6 of the Appendix.

Equations (1)–(3) are the fault modeling of the AMT, which will be employed in the following SA to generate the sequential residuals.

### 4 Fault Detectability and Isolability Analysis

In this section, a series of procedures will be presented to perform the SA so as to judge whether the sensor faults in the AMT can be detected or isolated, which is also a preliminary and vital process before designing the residuals. SA is a powerful tool for early determination of fault detectability properties for a given system [19,21].

#### 4.1 Fault Detectability Analysis (FDA)

There are two steps to execute FDA when utilizing the SA: structural representation and Dulmage–Mendelsohn (DM) decomposition.

##### 4.1.1 Structural Representation

Structural representation is an approach to visually display the structure of the model [22]. First, classify all the variables in fault modeling into three categories: unknown variables \{ia1, eb1, Tm1, TL1, Sf1, S1, ia2, eb2, Tm2, TL2, Sf2, S2, v1, o1, o2\}, known variables \{eA1, eA2, yA1, yA2, yA3, yST1, yST2, y1, y2, yv1\}, and faults variables \{fA1, fA2, fST1, fST2, f1, f2, fV1\}. Second, draw a bipartite graph with horizontal axis of all the variables and vertical axis of equations from \( e_1 \) to \( e_{20} \). Finally, mark the cross point as 1 if the equation contains the variable, otherwise mark 0.

Figure 3 shows the structural representation of the actuator given the system models (1)–(3). Here, “x” in bi-adjacency matrix means that if any variables or its time-derivatives appear in relevant equation. For example, two \( x \) appear in the equation of \( e_1 \), because variables of \( \{ia1, eb1, ea1\} \) are embodied in the equation of \( e_1 \).

#### 4.1.2 DM Decomposition

DM decomposition is an important tool to judge if a fault is structurally detectable. Here, structurally detectable is defined as follows [23]:

A fault \( f \) is structurally detectable in a model if

\[ ef \in M^+ \]  

(4)

where \( ef \) is the equation with fault \( f \), and \( M^+ \) is the structurally overdetermined (SO) part.

**Definition (SO).** A set of \( M \) of equations is SO if \( M \) has more equations than unknown variables [24].

From the above definitions, we can easily understand that if the equation in which a fault \( f \) appears lies in the SO part (\( M^+ \)), then the fault \( f \) will be detectable.

Figure 4 shows the DM decomposition result of the AMT model. We can see that all the faults lie in the overdetermined part, so all the faults are detectable.

#### 4.2 Fault Isolability Analysis (FIA)

Fault isolability means if a fault can be distinguished from the other faults when the fault happens. According to the definition in Ref. [23], a fault \( f_i \) is structurally isolable from \( f_j \) in a model \( M \) if

\[ ef \in (M \{ ef \})^+ \]  

(5)

where \( ef \) is the equation with fault \( f \), and \( M^+ \) is the structurally overdetermined (SO) part eliminating the equation of \( ef \). Equation (5) indicates that if we delete the equation in which the fault \( f_j \) appears, we can acquire another DM decomposition of the system without the fault of \( f_j \). If the fault \( f_i \) lies in the overdetermined part, then \( f_i \) is isolable to \( f_j \).

Using this methodology, we can obtain a fault isolability matrix (FIM), which can reflect the fault isolability intuitively.

Figure 5 shows the FIM of the AMT, where the symbol “x” means that the fault variables in horizontal and longitudinal are related, that is to say, they cannot be isolated from each other. We can see clearly that six faults \( \{fA1, fA2, fST1, fST2, f1, f2\} \) are uniquely isolated, remaining two faults \( \{fA2, fST2\} \) are isolable from the other faults but not isolable from each other.

<table>
<thead>
<tr>
<th>Table 1 Sensors description in the AMT</th>
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<tbody>
<tr>
<td><strong>Symbol</strong></td>
</tr>
<tr>
<td>( i_{a1} ) (ia1)</td>
</tr>
<tr>
<td>( S_1 ) (S1)</td>
</tr>
<tr>
<td>( S_{y1} ) (ST1)</td>
</tr>
<tr>
<td>( i_{a2} ) (ia2)</td>
</tr>
<tr>
<td>( S_2 ) (S2)</td>
</tr>
<tr>
<td>( o_1 ) (w1)</td>
</tr>
<tr>
<td>( o_2 ) (w2)</td>
</tr>
<tr>
<td>( V_i ) (V1)</td>
</tr>
</tbody>
</table>
5 Residual Design for Fault Diagnosis on the AMT

In this section, we will continue to utilize the SA techniques to discuss the residual design for health monitoring of the AMT. Before generating the residuals, finding minimal structurally overdetermined (MSO) sets of equations is a vital step because any MSO set can be a residual generator.

5.1 Finding MSO Sets. According to the definition in Ref. [24]: An SO set is a proper structurally overdetermined (PSO) set if \( M = M^+ \). An SO set is MSO set if no PSO subset is an SO set. An easy approach to find MSO is shown in Ref. [25]. The basic principle is choosing the first equation as a redundant equation in the overdetermined parts, then redraw the DM composition, and then get a new overdetermined part and corresponding equations. These equations are a member of the MSO sets. Then delete the second equation, another member of MSO sets can be obtained. By analogy, all the members of MSO sets can be found. This is a universal strategy to achieve the MSO sets, the drawback is that identical result can be repeated when eliminating the different equations, so the efficiency is low. Improved strategy can be found in Ref. [24].

Applying the methodology in Ref. [24], all the seven MSO sets can be obtained shown in Table 2 (right side). The symbol “/” in Table 2 means the fault can be detected in corresponding testable sets; the blank means the fault cannot be detected. For example, \( T_1 \) can detect two faults \( f_{S1} \) and \( f_{ST1} \), but not the other faults.

5.2 Residual Design. According to the conclusion by SA [22], every MSO set can generate a residual, so we can generate seven residuals because we have seven MSO sets. We will discuss the detailed procedures of residual design.

5.2.1 Residual 1. Residual 1 is deduced from \( T_1 \), which is made up of three equations \{\( e_5, e_7, e_8 \}\) in Eq. (1).

It is very easy to generate residual 1 from the three equations by substituting \( e_7 \) and \( e_8 \) into \( e_5 \), which is shown as follows:

\[
r_1 = y_{ST1}(t) - K_{F1} \cdot y_{S1}(t)
\]

where \( r_1 \) is residual 1.

5.2.2 Residual 2. Residual 2 is deduced from \( T_2 \), which is made up of four equations \{\( e_1, e_2, e_6, e_7 \}\) in Eq. (1). In order to get a unique and robust result of residual, the strategy of residual generator dynamics in Ref. [26] is employed here. The main procedures are as follows.

First, choose the equation with derivative as an ARR. Here, we only have \( e_1 \) as an ARR, which can be expressed in the following form:

\[
0 = -e_{a1} + L_{a1} \frac{dy_{a1}(t)}{dt} + R_{a1}y_{a1}(t) + K_{b1} \cdot \frac{dS_1(t)}{dt}
\]

Second, introduce an operator of \( (p + \beta)^q \) to replace the “0” at the left of the ARR equation to generate a residual-related equation. The result is shown in the following equation:

\[
(p + \beta)^q r_2 = -e_{a1} + L_{a1} \frac{dy_{a1}(t)}{dt} + R_{a1}y_{a1}(t) + K_{b1}K_1 \cdot \frac{dS_1(t)}{dt}
\]

where \( r_2 \) is residual 2, \( p \) is the differentiation operator, and \( q \) and \( \beta \) are the stable coefficients. In order to generate a stable residual, \( q \) should be chosen greater than the order of derivative at the right
part of ARR. Here, we set \( q = 1 \) because the order of right equation is 1. 

\( \beta \) should be greater than 0 for the stability of the system. Through the simulation of different value of \( \beta \), we obtain the magnitude of \( \beta \), which will affect the residual dynamics: Decreasing the size of \( \beta \) will improve the detectable sensitivity to the faults. Here, we choose \( \beta = 1 \).

Finally, define a state \( X_2 = (r_2 - L_{oa1}y_{oa1} - K_{oa1}K_{s1}) \) to resolve the residual from Eq. (10) through a basic observer canonical form state-space realization. Then, residual 2 can be generated shown in the following equation:

\[
X_2 = -\beta X_2 + [-1, R_{oa1} - \beta L_{oa1}, K_{oa1}K_{1}] \begin{bmatrix} e_{oa1} \\ y_{oa1} \\ y_{s1} \end{bmatrix}
\]

\[
r_2 = X_2 + [0, -K_{oa1}, -K_{oa1}K_{1}] \begin{bmatrix} e_{oa1} \\ y_{oa1} \\ y_{s1} \end{bmatrix}
\]

\[
\begin{align}
\dot{X}_3 &= \beta X_3 + [-1, R_{oa1} - \beta L_{oa1}, K_{oa1}K_{1}] \begin{bmatrix} e_{oa1} \\ y_{oa1} \\ y_{s1} \end{bmatrix} \\
0 &= -e_{oa1} + L_{oa1}\frac{dy_{oa1}(t)}{dt} + R_{oa1}y_{oa1}(t) + \frac{K_{oa1}K_1}{K_{f1}}\frac{dS_2(t)}{dt}
\end{align}
\]

Thus, residual 3 can be generated by the following equation:

\[
X_3 = \beta X_3 + [-1, R_{oa1} - \beta L_{oa1}, K_{oa1}K_{1}] \begin{bmatrix} e_{oa1} \\ y_{oa1} \\ y_{s1} \end{bmatrix}
\]

\[
r_3 = X_2 + [0, -K_{oa1}, -K_{oa1}K_{1}] \begin{bmatrix} e_{oa1} \\ y_{oa1} \\ y_{s1} \end{bmatrix}
\]

where \( r_3 \) is residual 3, and \( \beta > 0 \) for the stability of the system. Here, we set \( \beta = 1 \).

5.2.4 Residual 4. Residual 4 is deduced from \( T_k \), which is made up of four equations \( \{e_9, e_{10}, e_4, \text{ and } e_8\} \) in Eq. (2).

Applying the similar strategy to generate residual 2, an ARR is attained as follows:

\[
0 = -e_{oa2} + L_{oa2}\frac{dy_{oa2}(t)}{dt} + R_{oa2}y_{oa2}(t) + \frac{K_{oa2}K_2}{K_{f2}}\frac{dS_2(t)}{dt}
\]

Thus, residual 4 can be generated by the following equation:

\[
X_4 = \beta X_4 + [-1, R_{oa2} - \beta L_{oa2}, K_{oa2}K_2] \begin{bmatrix} e_{oa2} \\ y_{oa2} \\ y_{s2} \end{bmatrix}
\]

\[
r_4 = X_4 + [0, -K_{oa2}K_{2}, -K_{oa2}K_{1}] \begin{bmatrix} e_{oa2} \\ y_{oa2} \\ y_{s2} \end{bmatrix}
\]

where \( r_4 \) is residual 4, and \( \beta > 0 \) for the stability of the system. Here, we set \( \beta = 1 \).

5.2.5 Residual 5. Residual 5 is deduced from \( T_k \), which is made up of three equations \( \{e_{17}, e_{18}, \text{ and } e_{19}\} \) in Eq. (3). Employing the analogous approach to generate residual 1, residual 5 is easily acquired as follows:

\[
r_5 = y_{oa2}(t) - y_{oa1}(t) - G_R \cdot B_R - y_{oa1}(t)
\]

where \( r_5 \) is residual 5.

5.2.6 Residual 6. Residual 6 is deduced from \( T_k \), which is made up of three equations \( \{e_{16}, e_{17}, \text{ and } e_{20}\} \) of Eq. (3). Residual 6 is calculated by the following equation:

\[
r_6 = y_{oa2}(t) - y_{oa1}(t)/K_w
\]

where \( r_6 \) is residual 6.

5.2.7 Residual 7. Residual 7 is deduced from \( T_k \), which is made up of four equations \( \{e_{16}, e_{17}, e_{18}, \text{ and } e_{20}\} \) in Eq. (3). Residual 7 can be calculated by the following equation:

\[
r_7 = y_{oa1}(t) - y_{oa1}(t) \cdot G_R / K_w
\]

where \( r_7 \) is residual 7.

6 Experimental Evaluation

This section will explain the experimental evaluation for the proposed FDI scheme, and the seven designed residuals generated by the SA methodology will be tested by employing an offline approach of fault injection. Here, we do not implement faults online because of few unavoidable difficulties. One is that the injected faults may trigger the on-board diagnosis system to shut off the system or compensate for the fault. The other one is that the injected faults may lead to potential damage of the system or can be fatal for the driver, if we test the FDI scheme on the road [27]. Therefore, the offline strategy is chosen to cover the considered faults in a consistent way as well as to illustrate the proposed FDI scheme in this paper.

Figure 6 shows the detailed structure of the FDI system. The supervisory controller issues gear shift request to TCU which generates voltage duty cycles (\( e_{oa1} \) and \( e_{oa2} \)) to the actuators. The two actuators are equipped with five sensors, i.e., \( y_{s1}, y_{s1}, y_{s2}, y_{oa1}, \) and \( y_{oa2} \). These signals along with input shaft \( y_{oa1} \), output shaft \( y_{oa2} \), and vehicle speed \( y_{sp} \) are supplied to the developed FDI system.

Remark. As far as the real-time online fault detection is concerned, we believe our FDI scheme is also real-time implementable. However, we have some constraints to demonstrate the results. Figure 6 shows clearly how our FDI scheme will be used in the online system. We can extract the sensors signals from the real-time online system and plug into the proposed FDI system, which will deal with the signal processing and generate seven

<table>
<thead>
<tr>
<th>Table 2</th>
<th>MSO sets and minimal testable sets</th>
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</thead>
<tbody>
<tr>
<td>Minimal testable sets (MSO)</td>
<td>Equations</td>
</tr>
<tr>
<td>( f_{oa1} )</td>
<td>( f_{s1} )</td>
</tr>
<tr>
<td>( T_1 )</td>
<td>( T_2 )</td>
</tr>
</tbody>
</table>

Note: \( e_1 - e_{20} \) are the equations shown in Eqs. (1)-(3).
residual signals. Then, all these residual signals will be input into a residual observer, where there is a hardware controller which will compare the real-time signals with the healthy signals and then judge whether the signals cross the “threshold.” If the residuals lie within the threshold, the AMT will be declared as healthy; otherwise, there will be an alarm. Then, the methodology

### Table 3  Injected faults setting

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Time (s)</th>
<th>Type</th>
<th>Gear shift status</th>
</tr>
</thead>
<tbody>
<tr>
<td>( i_1 )</td>
<td>81–86</td>
<td>Bias</td>
<td>3–5</td>
</tr>
<tr>
<td>( S_1 )</td>
<td>121–126</td>
<td>Signals loss</td>
<td>5–3</td>
</tr>
<tr>
<td>ST1</td>
<td>190–195</td>
<td>Bias</td>
<td>3–5</td>
</tr>
<tr>
<td>( i_2 )</td>
<td>327–332</td>
<td>Disturbance</td>
<td>5–3</td>
</tr>
<tr>
<td>S2</td>
<td>417–422</td>
<td>Gain</td>
<td>3–5</td>
</tr>
<tr>
<td>W1</td>
<td>700–705</td>
<td>Signals loss</td>
<td>3–3</td>
</tr>
<tr>
<td>W2</td>
<td>900–905</td>
<td>Gain</td>
<td>5–5</td>
</tr>
<tr>
<td>( V_x )</td>
<td>1100–1105</td>
<td>Gain</td>
<td>6–6</td>
</tr>
</tbody>
</table>

residual signals. Then, all these residual signals will be input into a residual observer, where there is a hardware controller which will compare the real-time signals with the healthy signals and then judge whether the signals cross the “threshold.” If the residuals lie within the threshold, the AMT will be declared as healthy; otherwise, there will be an alarm. Then, the methodology
proposed in this paper will be employed to conclude where and what the fault is. The faults will be reported to TCU and then to the supervisor controller.

Figure 7 shows the gear shifting sequence during a city driving cycle. To investigate the influence of sensor faults, we inject the sensor faults when gear shift is requested.

Table 3 gives the detailed injected faults information, where we can see the duration, fault type, and gear shift status when the fault is introduced.

Figures 8–15 show the sensor signals under healthy operation and injected sensor faults. The solid line is the healthy data, which is measured by the online experiment, and the dashed line is the unhealthy data, which is simulated by the offline simulation that is consistent to the fault characters shown in Table 3.

Figures 16 and 17 show the X and Y actuators input voltage. Substituting the two voltage signals issued by TCU along with the above eight sensor signals into the FDI system, we can get the residuals response shown in Figs. 18–24.

Figures 18–20 show the fault detection result of X actuator, where we can see that residual 1 can detect the faults at the time of 121 s and 190 s; residual 2 can detect the faults at the time of...
327 s and 417 s. So, residual 4 can identify experiments conducted in simulation environment. For the evaluation of the proposed FDI scheme, we selected fixed values for the thresholds of all the residuals. The values of threshold refer to the analysis done prior to designing the residuals as shown in Table 2.

Furthermore, we can see that every residual is only sensitive to its corresponding faults and insensitive to the other faults which can help us to isolate the faults. Take the fault of “fia 1,” for example, if we assume that there is one fault at a time: when this fault happens, the state of the seven residuals will be “0110000”; in turn, if we find that the state of the seven residuals is like this, we can confirm that there is fault in current sensor at X actuator (because the fault of fia 1 denotes the fault of current sensor in X actuator). Because the state of the residuals to detect the six faults of (fia 1, fia 2, fia 3, fia 4, fia 5, and fia 6) are unique, these faults are isolable. But the state of the residuals for the two faults of (fia 2 and fia 3) are the same, so we cannot judge which fault happens, thus these two faults cannot be isolated from each other, but the state is different from the other faults, so the two faults are isolable from the other six faults. In conclusion, six faults of (fia 1, fia 2, fia 3, fia 4, fia 5, and fia 6) can be detected and isolated from the other six faults. The result is also consistent to the analysis shown in Fig. 5.

Remark. If we want the two faults of {fia 2, fia 3} uniquely isolable, we can install an L-lever angular displacement sensor (named ST 2) on Y actuator.

### Table 4: Detectability of the seven residuals

<table>
<thead>
<tr>
<th>Residual faults</th>
<th>R1</th>
<th>R2</th>
<th>R3</th>
<th>R4</th>
<th>R5</th>
<th>R6</th>
<th>R7</th>
</tr>
</thead>
<tbody>
<tr>
<td>fia 1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>fia 2</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>fia 3</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>fia 4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>fia 5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>fia 6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>fia 7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Note: Symbol “1” means the fault can be detected; “0” means the fault is not detectable.

Table 4 shows the summary of the fault detectability by the above seven residuals. The results show that every residual individually detects the designated faults, which is compatible to the analysis done prior to designing the residuals as shown in Table 2.

81 s and 121 s; and residual 3 can detect the faults at the time of 81 s and 190 s. Thus, residual 1 can identify fia 1 and fia 2, residual 2 can identify fia 3 and fia 4, and residual 3 can identify fia 5 and fia 6. 

For the evaluation of the proposed FDI scheme, we selected fixed values for the thresholds of all the residuals. The values of threshold are selected based on our understanding of the system and the experiments conducted in simulation environment.

Figure 21 displays the fault detection result of Y actuator, where we can observe that residual 4 can detect the faults at the time of 327 s and 417 s. So, residual 4 can identify fia 4 and fia 5.

Figures 22–24 demonstrate the fault detection result of transmission subsystem, where residual 5 can detect the faults at the time of 700 s and 900 s, residual 6 can detect the faults at the time of 900 s and 1100 s, and residual 7 can detect the faults at the time of 700 s and 1100 s. Thus, residual 5 can identify fia 3 and fia 4, residual 6 can identify fia 5 and fia 6, and residual 7 can identify fia 7.
Appendix

Table 5 Parameters for system model

<table>
<thead>
<tr>
<th>Name</th>
<th>Symbol</th>
<th>Unit</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>EM inductance (1 denotes X-direction actuator; 2 denotes Y-direction actuator, similarly hereinafter)</td>
<td>$L_{i1}$, $L_{i2}$</td>
<td>H</td>
<td>$5.144 \times 10^{-4}$</td>
</tr>
<tr>
<td>EM resistance</td>
<td>$R_{i1}$, $R_{i2}$</td>
<td>Ω</td>
<td>0.884</td>
</tr>
<tr>
<td>Back-emf constant</td>
<td>$K_{i1}$, $K_{i2}$</td>
<td>—</td>
<td>0.019</td>
</tr>
<tr>
<td>Torque constant</td>
<td>$K_{t1}$, $K_{t2}$</td>
<td>—</td>
<td>0.019</td>
</tr>
<tr>
<td>Displacement transferring constant</td>
<td>$k_{T1}$, $k_{T2}$</td>
<td>—</td>
<td>10.456</td>
</tr>
<tr>
<td>Displacement ratio of $S_{T1}/S_{T2}$ to $S_{1}/S_{2}$ constant</td>
<td>$K_{T1}$, $K_{T2}$</td>
<td>—</td>
<td>1.120</td>
</tr>
<tr>
<td>System equivalent inertia</td>
<td>$J_{e1}$, $J_{e2}$</td>
<td>kg m$^2$</td>
<td>$1.111 \times 10^{-5}$</td>
</tr>
<tr>
<td>System equivalent viscous coefficient</td>
<td>$B_{m1}$, $B_{m2}$</td>
<td>N m/rad</td>
<td>$1.287 \times 10^{-5}$</td>
</tr>
<tr>
<td>Armature current</td>
<td>$i_{a1}$, $i_{a2}$</td>
<td>A</td>
<td>—</td>
</tr>
<tr>
<td>Voltage of the power</td>
<td>$e_{a1}$, $e_{a2}$</td>
<td>V</td>
<td>—</td>
</tr>
<tr>
<td>The back emf</td>
<td>$e_{b1}$, $e_{b2}$</td>
<td>V</td>
<td>—</td>
</tr>
<tr>
<td>Rotor angular displacement</td>
<td>$\theta_{a1}$, $\theta_{a2}$</td>
<td>rad</td>
<td>—</td>
</tr>
<tr>
<td>Motor torque</td>
<td>$T_{e1}$, $T_{e2}$</td>
<td>N m</td>
<td>—</td>
</tr>
<tr>
<td>Load torque</td>
<td>$T_{L1}$, $T_{L2}$</td>
<td>N m</td>
<td>—</td>
</tr>
<tr>
<td>Actuator lead-screw displacement sensor</td>
<td>$S_{1}$, $S_{2}$</td>
<td>mm</td>
<td>—</td>
</tr>
<tr>
<td>Displacement of the transmission shaft</td>
<td>$S_{T1}$, $S_{T2}$</td>
<td>mm</td>
<td>—</td>
</tr>
<tr>
<td>Electric machine output shaft speed</td>
<td>$e_{a1}$ (w)</td>
<td>r/min</td>
<td>—</td>
</tr>
<tr>
<td>Transmission output shaft speed control</td>
<td>$e_{a2}$ (w)</td>
<td>r/min</td>
<td>—</td>
</tr>
<tr>
<td>Vehicle speed</td>
<td>$V_w$</td>
<td>km/h</td>
<td>—</td>
</tr>
<tr>
<td>Velocity transferring constant</td>
<td>$K_v$</td>
<td>—</td>
<td>0.032</td>
</tr>
<tr>
<td>Gear ratio (six-speed)</td>
<td>$G_R$</td>
<td>—</td>
<td>$D_V$: 3.818 $D_{V2}$: 2.158 $D_{V3}$: 1.475 $D_{V4}$: 1.067 $D_{V5}$: 0.875 $D_{V6}$: 0.744</td>
</tr>
<tr>
<td>Belt ratio</td>
<td>$B_R$</td>
<td>—</td>
<td>1.75</td>
</tr>
</tbody>
</table>

Table 6 Parameters for sensor variables and faults

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Name</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current sensor</td>
<td>Fault</td>
<td>$j_{ia1}$, $j_{ia2}$</td>
<td>($j_{ia1}, j_{ia2}$)</td>
</tr>
<tr>
<td>Lead-screw displacement sensor</td>
<td>Fault</td>
<td>$y_{ia1}$, $y_{ia2}$</td>
<td>($y_{ia1}, y_{ia2}$)</td>
</tr>
<tr>
<td>L-lever angular displacement sensor at X actuator</td>
<td>Fault</td>
<td>$s_{i1}$</td>
<td>($s_{i1}$)</td>
</tr>
<tr>
<td>Electric machine output shaft sensor</td>
<td>Measurement</td>
<td>$y_{ST1}$</td>
<td>($y_{ST1}$)</td>
</tr>
<tr>
<td>Transmission output shaft speed sensor</td>
<td>Fault</td>
<td>$y_{SV1}$</td>
<td>($y_{SV1}$)</td>
</tr>
<tr>
<td>Vehicle speed</td>
<td>Measurement</td>
<td>$y_{VS1}$</td>
<td>($y_{VS1}$)</td>
</tr>
</tbody>
</table>

References


