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Adaptive Observer-Based Fault Estimation for Switched Circuit Systems with Actuator and Sensor Faults

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Abstract: This paper investigates the simultaneous state and fault estimation problem for switched circuit systems subject to actuator faults, sensor faults, and external disturbances under an average dwell-time (ADT) switching law. First, a switched circuit model is established to describe the mode-dependent dynamics and the effects of different faults. Then, by incorporating the sensor-fault-related term into an augmented descriptor system, a multimode adaptive observer is developed to estimate the system states and unknown actuator and sensor faults. Furthermore, based on a mode-dependent Lyapunov function and the ADT switching technique, sufficient conditions are derived to guarantee the uniform ultimate boundedness of the estimation errors. Finally, numerical simulations and validation on a practical switched circuit platform are conducted to evaluate the state-estimation and fault-reconstruction performance of the developed observer. Simulation and experimental findings indicate the designed observer is capable of accurately tracking the system states and faults under switching operations and external disturbances.

Keywords: switched circuit systems; fault estimation; adaptive observer; actuator fault; sensor fault; average dwell time (ADT)

1. Introduction

Circuit systems have been widely employed in industrial applications and have therefore received extensive attention in the control community [1–3]. Various circuit configurations constitute a fundamental class because they naturally characterize the energy storage, energy dissipation, filtering, and transient response behaviors of practical electronic devices [4,5]. To mention a few, the switched circuit system in power converter applications was investigated in [6], while the circuit system in parameter-controlled tunnel diode circuit applications was studied in [7]. During long-term operation, circuit systems are prone to faults [8,9], which may seriously degrade the reliability of circuit systems. Therefore, fault estimation for circuit systems is of significant importance. Although existing studies on fault estimation for circuit systems are mainly limited to single-fault cases [10,11], practical systems may experience simultaneous faults involving different fault types. Hence, it is important to investigate the concurrent presence of both actuator and sensor faults within circuit systems.

Switched systems consist of multiple subsystems and a prescribed switching logic that regulates transitions among different modes. They have received substantial scholarly interest in the field of automatic control over the past few years [12,13]. Due to their effectiveness in representing com-

plex dynamic processes and simplifying controller synthesis, switched systems have found extensive applications in engineering domains, including DC–DC power converters and switched induction heater circuit systems [14,15]. For representative applications, ref. [14] developed a switched-affine control design framework for DC–DC converters. In [15], the stabilization of discretely sampled switched nonlinear systems under state-dependent switching was investigated and illustrated using a switched induction-heating circuit. Nevertheless, the presence of switching behavior inevitably affects the fault estimation performance of switched circuit systems, and existing single-mode observers [16,17] are generally inadequate for reconstructing faults in switched circuit systems. Despite this practical need, the design of multimode switched observers has received relatively limited attention, which motivates the present study.

Fault reconstruction aims to estimate the magnitude and time-varying profile of faults from available system measurements, rather than merely detecting the occurrence of faults [18,19]. For circuit systems, a number of significant results have been reported on fault reconstruction [20–22]. Representative approaches include the sliding mode observer proposed in [20] for fault reconstruction in circuit-based systems. In addition, ref. [21] developed a fuzzy fault-estimation scheme based on sampled measurements for nonlinear systems

with sampled-data outputs. However, most existing fault estimation observer designs for circuit systems rely on known upper bounds of faults [22,23]. Such prior information is often unavailable in practical circuit systems. This observation motivates constructing an adaptive observer-based fault estimation approach that can reconstruct unknown faults without relying on prescribed fault bounds.

Inspired by the preceding analysis, the present study addresses the observer synthesis problem concerning a category of switched circuit models affected by both actuator and sensor faults under the ADT switching law. The primary contributions of the present paper are outlined below.

- (1) Multiple-fault reconstruction mechanism for circuit systems: In contrast to the studies in [24,25], which addressed only fault estimation in circuit-system models involving a single fault category, the present study examines fault reconstruction in circuit-system models simultaneously affected by actuator and sensor faults. By introducing an augmented-system approach, the proposed observer can accurately reconstruct both the sensor fault appearing in the output equation and the actuator fault appearing in the state equation.
- (2) ADT-dependent multimode fault-estimation framework for switched circuit systems: Existing observer design methods for circuit systems, such as those in [26,27], were mainly developed for single-mode systems. To overcome this limitation, this study develops a multimode observer-based fault estimation scheme applicable to switched circuit models governed by an ADT switching mechanism. The developed approach is able to effectively attenuate the adverse influence of multimode switching behavior on fault reconstruction performance and maintain bounded estimation performance around switching instants.
- (3) Unknown-bound adaptive fault-reconstruction mechanism: The fault estimation schemes in [28,29] generally required the true upper bounds of faults, or even relied on specific fault forms and mainly focused on fault detection rather than fault reconstruction. In the present study, an adaptive observer-based fault estimation method is developed to address this restriction. By constructing suitable adaptive laws, the proposed design removes the requirement for known fault bounds and achieves accurate reconstruction of unknown faults in the considered circuit system.

The rest of this article is arranged as follows. Section 2 provides the system description and necessary preliminaries. A switched circuit model subject to actuator faults, sensor faults, and external disturbances is established, and an ADT switching rule is introduced. In Section 3, an augmented descriptor system is constructed to incorporate the sensor fault into the system state, and an adaptive observer is developed to achieve simultaneous state and fault estimation. Section 4 investigates the stability properties of the resulting estimation error system

and derives sufficient conditions to guarantee the uniform ultimate boundedness of the estimation errors under the ADT switching law. Section 5 presents numerical simulation results. Section 6 further verifies the proposed observer on a practical circuit platform. Finally, Section 7 concludes this paper.

2. System Description and Preliminaries

2.1. Problem Statement

To facilitate observer design, we consider the switched electronic circuit shown in Figure 1. The electrical network comprises inductors L_1 and L_2 , capacitors C_1 , C_2 , and C_3 , resistors R_1 , R_2 , and R_3 , and a controlled switch. The input voltage is denoted by $u_c(t)$, and $d(t)$ represents the external disturbance. Moreover, $f_a(t)$ and $f_s(t)$ denote the actuator fault and the sensor fault, respectively. The voltages across C_1 , C_2 , and C_3 are denoted by v_1 , v_2 , and v_3 , respectively, as shown in Figure 1. The variables i_1 and i_2 denote the currents flowing through inductors L_1 and L_2 , respectively. Based on fundamental circuit laws, the electrical network dynamics in Figure 1 can be derived as

$$\begin{cases} \dot{i}_1(t) = \frac{v_1(t) - v_2(t)}{L_1}, \\ \dot{i}_2(t) = \frac{v_2(t) - v_3(t)}{L_2}, \\ \dot{v}_1(t) = -\frac{i_1(t)}{C_1} + \frac{u_c(t) + f_a(t) - v_1(t)}{C_1 R_1}, \\ \dot{v}_2(t) = \frac{i_1(t) - i_2(t)}{C_2} - \frac{s(t)}{C_2 R_2} v_2(t), \\ \dot{v}_3(t) = \frac{i_2(t)}{C_3} + \frac{d(t) - v_3(t)}{C_3 R_3}, \end{cases} \quad (1)$$

where $s(t)$ is a switch-dependent coefficient defined by

$$s(t) = \begin{cases} 0, & \varsigma(t) = 1, \\ 1, & \varsigma(t) = 2, \end{cases} \quad (2)$$

and $\varsigma(t)$ is a piecewise-constant switching signal taking values in the finite set $\gamma = \{1, 2, \dots, M\}$. For the circuit considered in Figure 1, one has $M = 2$. When $\varsigma(t) = i$, the circuit is governed by the dynamics of the i th subsystem. The switching instant at which $\varsigma(t)$ changes its value is denoted by t_k . The value $s(t) = 1$ means that the branch associated with R_2 is connected to the node corresponding to $v_2(t)$, while $s(t) = 0$ means that this branch is disconnected.

Define the state vector $x(t)$, the measured output $y(t)$ affected by the sensor fault $f_s(t)$, and the control input $u_c(t)$ as

$$\begin{aligned} x(t) &= [i_1(t) \quad i_2(t) \quad v_1(t) \quad v_2(t) \quad v_3(t)]^T \\ y(t) &= [v_1(t) + f_s(t) \quad v_2(t) \quad v_3(t)]^T \\ u_c(t) &= V_c(t). \end{aligned} \quad (3)$$

Consequently, based on (1) and (3), the considered switched circuit system can be expressed as follows:

$$\begin{cases} \dot{x}(t) = A(\zeta(t))x(t) + B(\zeta(t))u_c(t) \\ \quad + B_a(\zeta(t))f_a(t) + F(\zeta(t))d(t), \\ y(t) = Cx(t) + D_s f_s(t), \end{cases} \quad (4)$$

where $d(t) \in \mathbf{R}^1$ denotes the external disturbance; $f_s(t) \in \mathbf{R}^1$ and $f_a(t) \in \mathbf{R}^1$ stand for the unknown sensor fault and actuator fault, respectively; the mode-dependent matrices $A(\zeta(t))$, $B(\zeta(t))$, $B_a(\zeta(t))$, and $F(\zeta(t))$ are denoted by A_i , B_i , B_{ai} , and F_i , respectively, when $\zeta(t) = i$. The constant output matrix and sensor-fault distribution matrix are denoted by C and D_s , respectively. The corresponding matrices in (4) are given by

$$A_i = \begin{bmatrix} 0 & 0 & \frac{1}{L_1} & -\frac{1}{L_1} & 0 \\ 0 & 0 & 0 & \frac{1}{L_2} & -\frac{1}{L_2} \\ -\frac{1}{C_1} & 0 & -\frac{1}{C_1 R_1} & 0 & 0 \\ \frac{1}{C_2} & -\frac{1}{C_2} & 0 & -\frac{s(t)}{C_2 R_2} & 0 \\ 0 & \frac{1}{C_3} & 0 & 0 & -\frac{1}{C_3 R_3} \end{bmatrix}, \quad (5)$$

$$B_i = B_{ai} = \begin{bmatrix} 0 & 0 & \frac{1}{C_1 R_1} & 0 & 0 \end{bmatrix}^T,$$

$$F_i = \begin{bmatrix} 0 & 0 & 0 & 0 & \frac{1}{C_3 R_3} \end{bmatrix}^T,$$

$$C = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}, D_s = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}.$$

where $i = 1, 2$ applies to the mode-dependent matrices A_i , B_i , B_{ai} , and F_i .

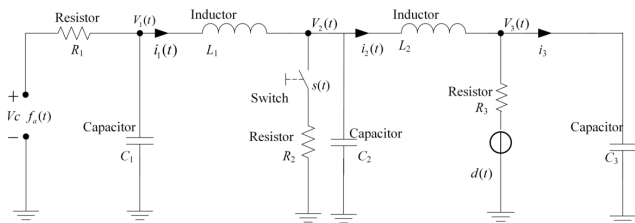


Figure 1. The switched electronic circuit with the actuator fault $f_a(t)$, sensor fault $f_s(t)$, and external disturbance $d(t)$.

In the subsequent sections, the observer design and stability analysis are developed for the general switched system (4) with compatible dimensions. This study adopts the following assumptions.

Assumption 1. The unknown external disturbance $d(t)$ and the unknown sensor fault $f_s(t)$ are norm bounded, that is,

$$\|d(t)\| \leq \bar{d}, \quad \|f_s(t)\| \leq \bar{f}_s, \quad (6)$$

where $\bar{d}$ and $\bar{f}_s$ are unknown positive constants. In addition, the sensor fault $f_s(t)$ is assumed to be continuous at each switching instant t_k , i.e., $f_s(t_k^+) = f_s(t_k^-)$. Moreover, there exists an unknown positive constant $\bar{\psi}$ satisfying

$$\bar{d} + \bar{f}_s \leq \bar{\psi}. \quad (7)$$

Assumption 2. For the time-varying actuator fault $f_a(t)$, there exist unknown positive scalars $\bar{f}$ and $\bar{\dot{f}}$ such that

$$|f_a(t)| \leq \bar{f}, \quad |\dot{f}_a(t)| \leq \bar{\dot{f}}. \quad (8)$$

Assumption 3. The matrix D_s has full column rank. Furthermore, the rank condition below is satisfied

$$\text{rank} \begin{bmatrix} B_{ai} & F_i \end{bmatrix} = \text{rank} \left(C \begin{bmatrix} B_{ai} & F_i \end{bmatrix} \right). \quad (9)$$

Lemma 1. The switching signal $\zeta(t)$ is said to satisfy the ADT condition with a constant $\tau_a > 0$ if, for any $t > t_0 \geq 0$, the number of switchings $N_\zeta(t_0, t)$ over the interval $[t_0, t)$ satisfies

$$N_\zeta(t_0, t) \leq N_0 + \frac{t - t_0}{\tau_a}, \quad \forall t > t_0 \geq 0, \quad (10)$$

where $N_0 \geq 0$ is the chatter bound.

The switched-system representation of electrical circuits has a direct engineering interpretation. For example, ref. [30] modeled a DC–DC buck–boost converter as a switched system, where the controlled switch alternates between open and closed states, resulting in different circuit topologies and subsystem dynamics. Similarly, ref. [15] applied state-dependent switching to an induction-heater circuit to achieve closed-loop stabilization. In the circuit considered in this paper, $\zeta(t)$ represents the operating state of the controlled switch, which connects or disconnects the branch associated with R_2 , thereby generating two mode-dependent circuit configurations.

The ADT condition provides a flexible framework for characterizing admissible switching behaviors in practical switched circuits [31,32]. Unlike the conventional dwell-time condition, which imposes a minimum time interval between any two consecutive switching instants, the ADT condition restricts only the average number of switching events over a given time interval. Therefore, the switching sequence can be nonperiodic and irregular, provided that $N_\zeta(t_0, t) \leq N_0 + (t - t_0)/\tau_a$ is satisfied. This relatively relaxed requirement makes the ADT framework suitable for practical switching circuits, where the switching instants may vary during operation. The ADT condition is not intended to describe the physical switching mechanism itself; rather, it specifies a class of admissible switching signals under which the stability of the proposed observer can be theoretically guaranteed.

Remark 1. Some existing fault estimation observer design methods in [28] and [29] require the a priori knowledge of the bounds or specific structures of fault signals. Such information, however, is usually difficult to obtain in practical circuit systems. In this paper, the exact trajectories of the actuator fault, sensor fault, and external disturbance are assumed to be unknown. The proposed adaptive observer is designed under this setting, which relaxes the requirement on precise fault information.

3. Adaptive Observer Design

To enable simultaneous reconstruction, the augmented vector is defined as $\bar{x}(t) = [x(t)^T (D_s f_s(t))^T]^T \in \mathbf{R}^8$. Based on the above augmentation, the resulting system takes the following form:

$$\begin{cases} \bar{E}\dot{\bar{x}}(t) = \bar{A}_i\bar{x}(t) + \bar{B}_i u_c(t) + \bar{B}_{ai} f_a(t) + \bar{F}_i \phi(t), \\ y(t) = \bar{C}\bar{x}(t), \end{cases} \quad (11)$$

where

$$\begin{aligned} \phi(t) &= \begin{bmatrix} d(t) \\ f_s(t) \end{bmatrix}, \bar{E} = \begin{bmatrix} I_n & 0 \\ 0 & 0_p \end{bmatrix}, \bar{A}_i = \begin{bmatrix} A_i & 0 \\ 0 & -I_p \end{bmatrix}, \\ \bar{B}_i &= \begin{bmatrix} B_i \\ 0 \end{bmatrix}, \bar{C} = \begin{bmatrix} C & I_p \end{bmatrix}, \\ \bar{B}_{ai} &= \begin{bmatrix} B_{ai} \\ 0 \end{bmatrix}, \bar{F}_i = \begin{bmatrix} F_i & 0 \\ 0 & D_s \end{bmatrix}, \end{aligned} \quad (12)$$

and the vector $\phi(t)$ is bounded as $\|\phi(t)\| \leq \bar{\psi}$ from (7).

To estimate the system states $\bar{x}(t)$ and the faults in (11), the observer is formulated as follows:

$$\begin{cases} \dot{\hat{z}}(t) = (\bar{A}_i - L_{pi}\bar{C})\hat{x}(t) + \bar{B}_i u_c(t) \\ \quad + \bar{B}_{ai}\hat{f}_a(t) + L_{pi}y(t) + L_{\phi i}u_\phi(t), \\ \hat{x}(t) = \bar{S}^{-1}(\hat{z}(t) + L_D y(t)), \end{cases} \quad (13)$$

where $\hat{z}(t) \in \mathbf{R}^8$ denotes an auxiliary variable; $\hat{x}(t) \in \mathbf{R}^8$ denotes the estimate of $\bar{x}(t)$; $\hat{f}_a(t) \in \mathbf{R}^1$ represents the estimate of the actuator fault $f_a(t)$; the observer input $u_\phi(t) \in \mathbf{R}^2$ will be given later; $\bar{S} = \bar{E} + L_D \bar{C} \in \mathbf{R}^{8 \times 8}$, $L_D \in \mathbf{R}^{8 \times 3}$, $L_{pi} \in \mathbf{R}^{8 \times 3}$ and $L_{\phi i} \in \mathbf{R}^{8 \times 2}$ are the observer gains to be designed.

We choose $L_D = [0 \quad I_3]^T$. Then, $\bar{S} = \bar{E} + L_D \bar{C} = \begin{bmatrix} I_5 & 0 \\ C & I_3 \end{bmatrix}$, which is nonsingular.

The observer input $u_\phi(t)$ in (13) is constructed as

$$u_\phi(t) = -\frac{\hat{\phi}^2(t) R_{2i} (\bar{C}\hat{x}(t) - y(t))}{|\hat{\phi}(t)| \|\bar{C}\hat{x}(t) - y(t)\| + \varrho(t)}, \quad (14)$$

where $\hat{\phi}(t) \in \mathbf{R}^1$ is the estimate of the unknown bound $\bar{\psi}$ defined in Assumption 1; $R_{2i} \in \mathbf{R}^{2 \times 3}$ denotes the design matrix; $\varrho(t) = b_0 e^{-b_1 t}$, where both $b_0 > 0$ and $b_1 > 0$ are constants.

Subsequently, the adaptive laws of $\hat{f}_a(t)$ and $\hat{\phi}(t)$ are formulated as

$$\begin{aligned} \dot{\hat{f}}_a(t) &= -v_1 R_{1i} [\bar{C}\hat{x}(t) - y(t)] - v_2 \hat{f}_a(t), \\ \dot{\hat{\phi}}(t) &= cd_1 \left[\|\bar{C}\hat{x}(t) - y(t)\| - cd_2 \hat{\phi}(t) \right], \end{aligned} \quad (15)$$

where v_1 , v_2 , cd_1 , and cd_2 are positive scalars to be selected.

The estimation error vectors are defined as

$$\begin{aligned} \bar{e}(t) &= \hat{x}(t) - \bar{x}(t), e_{fa}(t) = \hat{f}_a(t) - f_a(t), \\ \tilde{\phi}(t) &= \hat{\phi}(t) - \bar{\psi}. \end{aligned} \quad (16)$$

Considering the observer (13) with the intermediate variable $\hat{z}(t)$, we have

$$\begin{aligned} \bar{S}\dot{\hat{x}}(t) &= \dot{\hat{z}}(t) + L_D \dot{y}(t) \\ &= (\bar{A}_i - L_{pi}\bar{C})\hat{x}(t) + L_{pi}y(t) + L_{\phi i}u_\phi(t) \\ &\quad + \bar{B}_{ai}\hat{f}_a(t) + \bar{B}_i u_c(t) + L_D \bar{C}\dot{\hat{x}}(t). \end{aligned} \quad (17)$$

Recalling $\hat{x}(t)$ in (13) and $\bar{S} = \bar{E} + L_D \bar{C}$, it follows that

$$\begin{aligned} \bar{S}\dot{\hat{x}}(t) &= \bar{A}_i\bar{x}(t) + \bar{B}_i u_c(t) + \bar{B}_{ai} f_a(t) \\ &\quad + \bar{F}_i \phi(t) + L_D \bar{C}\dot{\hat{x}}(t). \end{aligned} \quad (18)$$

Then, by selecting $L_{\phi i} = \bar{F}_i$ and using (17) and (18), we obtain the following error system:

$$\begin{aligned} \dot{\bar{e}}(t) &= \bar{S}^{-1}(\bar{A}_i - L_{pi}\bar{C})\bar{e}(t) + \bar{S}^{-1}\bar{B}_{ai}e_{fa}(t) \\ &\quad + \bar{S}^{-1}L_{\phi i}(u_\phi(t) - \phi(t)). \end{aligned} \quad (19)$$

4. Stability Analysis of Error Dynamics

This section analyzes the stability properties of the estimation error system.

Theorem 1. For the error dynamics (19), if there exist positive definite matrices $P_i \in \mathbf{R}^{8 \times 8}$, a positive scalar ε , and matrices $L_{pi} \in \mathbf{R}^{8 \times 3}$, $R_{1i} \in \mathbf{R}^{1 \times 3}$, $R_{2i} \in \mathbf{R}^{2 \times 3}$, for $i \in \gamma$, such that

$$\begin{aligned} P_i \bar{S}^{-1}(\bar{A}_i - L_{pi}\bar{C}) + (\bar{A}_i - L_{pi}\bar{C})^T (\bar{S}^{-1})^T P_i \\ + \varepsilon P_i < 0, \end{aligned} \quad (20)$$

$$\bar{B}_{ai}^T (\bar{S}^{-1})^T P_i = R_{1i} \bar{C}, \quad (21)$$

$$L_{\phi i}^T (\bar{S}^{-1})^T P_i = R_{2i} \bar{C}, \quad (22)$$

then the estimation errors in (19) are uniformly ultimately bounded, provided that the ADT τ_a satisfies

$$\tau_a > \tau_a^* = \frac{\ln \mu}{\beta}, \quad (23)$$

where $\mu = \max \left\{ \sup_{i,j \in \gamma} \left\| P_i^{\frac{1}{2}} P_j^{-\frac{1}{2}} \right\|^2, b \right\}$, with $b > 1$ being a prescribed constant chosen sufficiently close to 1. Furthermore, $\beta = \min \{\varepsilon, v_2 - \alpha_0, cd_1 cd_2\}$, where α_0 is a positive scalar satisfying $0 < \alpha_0 \leq v_2$.

Proof. Let the Lyapunov functions be given by

$$V_i(t) = V_{1i}(t) + V_2(t) + V_3(t), \quad (24)$$

where

$$V_{1i}(t) = \bar{e}^T(t) P_i \bar{e}(t), V_2(t) = \frac{e_{fa}^2(t)}{v_1}, V_3(t) = \frac{\tilde{\phi}^2(t)}{cd_1}. \quad (25)$$

Subsequently, for $t \in [t_k, t_{k+1})$, where t_k denotes the k -th switching instant, one obtains

$$\begin{aligned}\dot{V}_{i1}(t) = & \bar{e}^T(t) \left[P_i \bar{S}^{-1} (\bar{A}_i - L_{pi} \bar{C}) \right. \\ & + (\bar{A}_i - L_{pi} \bar{C})^T (\bar{S}^{-1})^T P_i \left. \right] \bar{e}(t) \\ & + 2\bar{e}^T(t) P_i \bar{S}^{-1} \bar{B}_{ai} e_{fa}(t) \\ & + 2\bar{e}^T(t) P_i \bar{S}^{-1} L_{\phi i} (u_\phi(t) - \phi(t)).\end{aligned}\quad (26)$$

From the adaptive law of $\hat{f}_a(t)$ given in (15), we have

$$\begin{aligned}\dot{V}_2(t) &= 2 \frac{e_{fa}(t)}{v_1} \left(\dot{\hat{f}}_a(t) - \dot{f}_a(t) \right) \\ &= -2 \left[\frac{1}{v_1} e_{fa}(t) \dot{f}_a(t) + \frac{v_2}{v_1} e_{fa}(t) \hat{f}_a(t) \right. \\ &\quad \left. + e_{fa}(t) R_{1i} (\bar{C} \hat{x}(t) - y(t)) \right].\end{aligned}\quad (27)$$

By applying Young's inequality, for any scalar $0 < \alpha_0 \leq v_2$, it follows that

$$-\frac{2}{v_1} e_{fa}(t) \dot{f}_a(t) \leq \frac{\alpha_0}{v_1} e_{fa}^2(t) + \frac{1}{\alpha_0 v_1} \dot{f}_a^2(t). \quad (28)$$

Furthermore, the term $\frac{-2v_2}{v_1} e_{fa}(t) \hat{f}_a(t)$ in (27) can be rewritten as

$$\begin{aligned}& \frac{-2v_2}{v_1} e_{fa}(t) \hat{f}_a(t) \\ &= -\frac{2v_2}{v_1} e_{fa}(t) (f_a(t) + e_{fa}(t)) \\ &\leq -\frac{v_2}{v_1} e_{fa}^2(t) + \frac{v_2}{v_1} f_a^2(t).\end{aligned}\quad (29)$$

Considering the term $2\bar{e}^T(t) P_i \bar{S}^{-1} \bar{B}_{ai} e_{fa}(t)$ in (26) and the equation (21), we can establish the result that

$$\begin{aligned}& 2\bar{e}^T(t) P_i \bar{S}^{-1} \bar{B}_{ai} e_{fa}(t) \\ &= 2\bar{e}^T(t) \bar{C}^T R_{1i}^T e_{fa}(t) \\ &= 2e_{fa}(t) R_{1i} \bar{C} \bar{e}(t).\end{aligned}\quad (30)$$

Using the results from (27)–(30) and $|f_a(t)| \leq \bar{f}$, $|\dot{f}_a(t)| \leq \bar{f}$ in (8), we can obtain that

$$\begin{aligned}& 2\bar{e}^T(t) P_i \bar{S}^{-1} \bar{B}_{ai} e_{fa}(t) + \dot{V}_2(t) \\ &\leq \frac{\alpha_0}{v_1} e_{fa}^2(t) - \frac{v_2}{v_1} e_{fa}^2(t) + \frac{1}{\alpha_0 v_1} \dot{f}_a^2(t) + \frac{v_2}{v_1} f_a^2(t) \\ &\leq -\frac{v_2 - \alpha_0}{v_1} e_{fa}^2(t) + \frac{v_2}{v_1} \bar{f}^2 + \frac{1}{\alpha_0 v_1} \bar{f}^2.\end{aligned}\quad (31)$$

Based on the adaptive law of $\hat{\phi}(t)$ in (15), $\dot{V}_3(t)$ can be reformulated as

$$\begin{aligned}\dot{V}_3(t) &= 2\tilde{\phi}(t) \|R_{2i}(\bar{C} \hat{x}(t) - y(t))\| - 2cd_2 \tilde{\phi}(t) \hat{\phi}(t) \\ &\leq 2\tilde{\phi}(t) \|R_{2i}(\bar{C} \hat{x}(t) - y(t))\| - cd_2 \tilde{\phi}^2(t) + cd_2 \bar{\psi}^2.\end{aligned}\quad (32)$$

From the input term $u_\phi(t)$ in (14) and the equality in (22), we have

$$\begin{aligned}& 2\bar{e}^T(t) P_i \bar{S}^{-1} L_{\phi i} (u_\phi(t) - \phi(t)) \\ &= -\frac{2\hat{\phi}^2(t) \|R_{2i}(\bar{C} \hat{x}(t) - y(t))\|^2}{|\hat{\phi}(t)| \|R_{2i}(\bar{C} \hat{x}(t) - y(t))\| + \varrho(t)} \\ &\quad - 2\hat{\phi}^T(t) R_{2i} \bar{C} \bar{e}(t) \\ &\leq -\frac{2\hat{\phi}^2(t) \|R_{2i}(\bar{C} \hat{x}(t) - y(t))\|^2}{|\hat{\phi}(t)| \|R_{2i}(\bar{C} \hat{x}(t) - y(t))\| + \varrho(t)} \\ &\quad + 2\bar{\psi} \|R_{2i}(\bar{C} \hat{x}(t) - y(t))\|.\end{aligned}\quad (33)$$

According to (32) and (33), it follows that

$$\begin{aligned}& 2\bar{e}^T(t) P_i \bar{S}^{-1} L_{\phi i} (u_\phi(t) - \phi(t)) + \dot{V}_3(t) \\ &\leq 2|\hat{\phi}(t)| \|R_{2i}(\bar{C} \hat{x}(t) - y(t))\| - cd_2 \tilde{\phi}^2(t) + cd_2 \bar{\psi}^2 \\ &\quad - 2|\hat{\phi}(t)| \|R_{2i}(\bar{C} \hat{x}(t) - y(t))\| \\ &\quad \times \left(1 - \frac{\varrho(t)}{|\hat{\phi}(t)| \|R_{2i}(\bar{C} \hat{x}(t) - y(t))\| + \varrho(t)} \right) \\ &= \frac{2\varrho(t) |\hat{\phi}(t)| \|R_{2i}(\bar{C} \hat{x}(t) - y(t))\|}{|\hat{\phi}(t)| \|R_{2i}(\bar{C} \hat{x}(t) - y(t))\| + \varrho(t)} \\ &\quad - cd_2 \tilde{\phi}^2(t) + cd_2 \bar{\psi}^2 \\ &\leq -cd_2 \tilde{\phi}^2(t) + cd_2 \bar{\psi}^2 + 2b_0.\end{aligned}\quad (34)$$

Based on (20), (26), (31), and (34), the following inequality holds:

$$\begin{aligned}\dot{V}_i(t) \leq & \bar{e}^T(t) \left[P_i \bar{S}^{-1} (\bar{A}_i - L_{pi} \bar{C}) \right. \\ & + (\bar{A}_i - L_{pi} \bar{C})^T (\bar{S}^{-1})^T P_i + \varepsilon P_i \left. \right] \bar{e}(t) \\ & - \varepsilon \bar{e}^T(t) P_i \bar{e}(t) - \frac{cd_1 cd_2}{cd_1} \tilde{\phi}^2(t) - \frac{v_2 - \alpha_0}{v_1} e_{fa}^2(t) \\ & + \frac{v_2}{v_1} \bar{f}^2 + \frac{1}{\alpha_0 v_1} \bar{f}^2 + cd_2 \bar{\psi}^2 + 2b_0 \\ & \leq -\beta V_i(t) + \beta_0,\end{aligned}\quad (35)$$

where

$$\begin{aligned}\beta &= \min\{\varepsilon, v_2 - \alpha_0, cd_1 cd_2\}, \\ \beta_0 &= \frac{v_2}{v_1} \bar{f}^2 + \frac{1}{\alpha_0 v_1} \bar{f}^2 + cd_2 \bar{\psi}^2 + 2b_0.\end{aligned}$$

Considering $V_{i1}(t) = \bar{e}^T(t) P_i \bar{e}(t)$, when $V_{i1}(t)$ undergoes a jump at each switching instant t_k , it can be expressed as

$$\begin{aligned}V_{i1}(t_k^+) &= \|P_i^{\frac{1}{2}} \bar{e}(t_k^+)\|^2 \\ &\leq \|P_i^{\frac{1}{2}} P_j^{-\frac{1}{2}}\|^2 \|P_j^{\frac{1}{2}} \bar{e}(t_k^-)\|^2 \\ &\leq \mu V_{j1}(t_k^-),\end{aligned}\quad (36)$$

where $\mu = \max \left\{ \sup_{i,j \in \gamma} \|P_i^{\frac{1}{2}} P_j^{-\frac{1}{2}}\|^2, b \right\}$ is defined in (23), $\varsigma(t_k^+) = i$, $\varsigma(t_k^-) = j$, for $i, j \in \gamma$. Then, from (24), we have

$$V_i(t_k^+) \leq \mu V_j(t_k^-). \quad (37)$$

For a given time horizon $[0, T]$, where $T > 0$, define $t_0 = 0$ and let $t_1, t_2, \dots, t_{N_\varsigma(T,0)}$ represent all switching instants generated by the switching signal $\varsigma(t)$. The quantity $N_\varsigma(T, 0)$ denotes the cumulative number of switching events on $[0, T]$. Define $X(t) = [\bar{e}^T(t) \ e_{fa}^T(t) \ \tilde{\phi}(t)]^T$. Introduce the analytical expression

$$\Phi(t) = e^{\beta t} V_{\varsigma(t)}(X(t)). \quad (38)$$

Since $V_{\varsigma(t)}(X(t))$ is continuously differentiable over each interval $[t_k, t_{k+1})$, we have

$$\begin{aligned} & \Phi(T^-) \\ & \leq \Phi(t_{N_\varsigma(T,0)}) + \int_{t_{N_\varsigma(T,0)}}^T \beta_0 e^{\beta t} dt \\ & \leq \mu \left[\Phi(t_{N_\varsigma(T,0)-1}) + \int_{t_{N_\varsigma(T,0)-1}}^{t_{N_\varsigma(T,0)}} \beta_0 e^{\beta t} dt + \mu^{-1} \int_{t_{N_\varsigma(T,0)}}^T \beta_0 e^{\beta t} dt \right] \\ & \leq \mu^{N_\varsigma(T,0)} \Phi(0) + \sum_{s=0}^{N_\varsigma(T,0)-1} \mu^{N_\varsigma(T,0)-s} \int_{t_s}^{t_{s+1}} \beta_0 e^{\beta t} dt \\ & \quad + \int_{t_{N_\varsigma(T,0)}}^T \beta_0 e^{\beta t} dt. \end{aligned} \quad (41)$$

where $N_\varsigma(T, 0)$ denotes the number of switching events over the interval $[0, T]$.

To facilitate the analysis, we define an auxiliary positive parameter ξ such that $\xi \in (0, \beta - \frac{\ln \mu}{\tau_a})$. Consequently, the inequality $0 \leq \xi \leq \beta$ holds. Considering the term $\int_{t_s}^{t_{s+1}} \beta_0 e^{\beta t} dt$ in (41), we obtain

$$\begin{aligned} & \int_{t_s}^{t_{s+1}} \beta_0 e^{\beta t} dt \\ & = e^{\beta t_{s+1}} \int_{t_s}^{t_{s+1}} \beta_0 e^{\beta(t-t_{s+1})} dt \\ & \leq e^{(\beta-\xi)t_{s+1}} \int_{t_s}^{t_{s+1}} \beta_0 e^{\xi t} dt. \end{aligned} \quad (42)$$

Recalling $N_\varsigma(T, t) \leq N_0 + \frac{T-t}{\tau_a}$ in (10), the term $\mu^{N_\varsigma(T,0)-s}$ in (41) can be enlarged as

$$\begin{aligned} & \mu^{N_\varsigma(T,0)-s} \\ & \leq \mu^{1+N_0+\frac{T-t_{s+1}}{\tau_a}} \\ & \leq \mu^{1+N_0} e^{(\beta-\xi)(T-t_{s+1})}. \end{aligned} \quad (43)$$

Using the results from (41)–(43), we can establish that

$$\begin{aligned} & \Phi(T^-) \\ & \leq \sum_{s=0}^{N_\varsigma(T,0)-1} \mu^{1+N_0} e^{(\beta-\xi)T} \int_{t_s}^{t_{s+1}} \beta_0 e^{\xi t} dt \\ & \quad + \mu^{N_\varsigma(T,0)} \Phi(0) + \int_{t_{N_\varsigma(T,0)}}^T \beta_0 e^{\xi t} dt \\ & \leq \mu^{N_\varsigma(T,0)} \Phi(0) + \mu^{1+N_0} \frac{\beta_0}{\xi} (1 - e^{-\xi T}). \end{aligned} \quad (44)$$

$$\dot{\Phi}(t) = \beta e^{\beta t} V_{\varsigma(t)}(X(t)) + e^{\beta t} \dot{V}_{\varsigma(t)}(X(t)) \leq \beta_0 e^{\beta t}. \quad (39)$$

Considering the term (37), we have

$$\begin{aligned} \Phi(t_{j+1}) & = e^{\beta t_{j+1}} V_{\varsigma(t_{j+1})}(X(t_{j+1})) \\ & \leq \mu \Phi(t_{j+1}^-) \\ & \leq \mu \left[\Phi(t_j) + \int_{t_j}^{t_{j+1}} \beta_0 e^{\beta t} dt \right]. \end{aligned} \quad (40)$$

Furthermore, during the period $[0, T]$, it can be shown that

For the term $V_{\varsigma(t)}(X(t))$, one obtains $\underline{L}(\|X(t)\|) \leq V_{\varsigma(t)}(X(t)) \leq \bar{L}(\|X(t)\|)$, where $0 \leq \underline{L} \leq \bar{L}$. Therefore, in view of (42)–(44), the term $V_{\varsigma(T-)}(X(T))$ can be extended to

$$\begin{aligned} & V_{\varsigma(T-)}(X(T)) \\ & \leq e^{N_0 \ln \mu} e^{(\frac{\ln \mu}{\tau_a} - \beta)T} \bar{L}(\|X(0)\|) + \mu^{1+N_0} \frac{\beta_0}{\xi} (1 - e^{-\xi T}) \\ & \leq e^{N_0 \ln \mu} e^{(\frac{\ln \mu}{\tau_a} - \beta)T} \bar{L}(\|X(0)\|) + \mu^{1+N_0} \frac{\beta_0}{\xi}. \end{aligned} \quad (45)$$

Considering $T \rightarrow \infty$, one obtains that

$$V_{\varsigma(T-)}(X(T)) \leq \mu^{1+N_0} \frac{\beta_0}{\xi}. \quad (46)$$

Furthermore, we have

$$\begin{aligned} \|\bar{e}(t)\| & \leq \sqrt{\mu^{1+N_0} \frac{\beta_0}{\xi \lambda_{\min}\{P_i\}}}, \\ \|e_{fa}(t)\| & \leq \sqrt{\mu^{1+N_0} \frac{\beta_0 \max\{v_1\}}{\xi \lambda_{\min}\{P_i\}}}, \end{aligned} \quad (47)$$

which implies that, provided the switching condition (23) holds, the estimation errors $\bar{e}(t)$ and $e_{fa}(t)$ are uniformly ultimately bounded and eventually remain within a bounded neighborhood of the origin as $T \rightarrow \infty$.

Theorem 1 yields an estimate $\hat{x}(t)$ of $\bar{x}(t)$, together with the actuator-fault estimate $\hat{f}_a(t)$. Using the augmented-state definition given in (12), the plant state and auxiliary variable associated with the measurement fault are recovered via

$$\hat{x}(t) = [I_5 \ 0_{5 \times 3}] \hat{\bar{x}}(t), \quad \hat{\eta}_s(t) = [0_{3 \times 5} \ I_3] \hat{\bar{x}}(t), \quad (48)$$

where $\hat{\eta}_s(t)$ denotes the estimate of $D_s f_s(t)$.

Since Assumption 3 requires D_s to possess maximal column rank, a left inverse of D_s exists. Hence, the measurement fault is recovered according to

$$\begin{aligned}\hat{f}_s(t) &= (D_s^T D_s)^{-1} D_s^T \hat{\eta}_s(t) \\ &= (D_s^T D_s)^{-1} D_s^T [0_{3 \times 5} \quad I_3] \hat{x}(t).\end{aligned}\quad (49)$$

This completes the proof of Theorem 1. $\square$

Remark 2. It should be emphasized that the stability result established in Theorem 1 is uniform ultimate boundedness rather than asymptotic convergence to zero. Similar boundedness conclusions for ADT-based adaptive switched systems have also been reported in [33, 34]. In these studies, the closed-loop signals are guaranteed to remain bounded, while the corresponding estimation or tracking errors approach a neighborhood of the origin rather than necessarily converging exactly to zero. Specifically, under the prescribed ADT condition, the effect of the initial conditions decays with time. Meanwhile, the estimation errors eventually remain within a bounded neighborhood of the origin, whose size is characterized by the bounds in (47). Therefore, the estimation errors are not required to converge exactly to zero.

Remark 3. It should be noted that the derived stability conditions are sufficient rather than necessary and therefore involve a certain degree of conservatism. The ADT condition imposes a lower bound on the admissible average dwell time through $\tau_a > \ln(\mu)/\beta$ in (23). Moreover, $\beta = \min\{\varepsilon, v_2 - \alpha_0, cd_1 cd_2\}$ in (35) is taken as the smallest coefficient in the Lyapunov inequality, which is a conservative choice. The relaxation variables are introduced mainly for computational tractability, and the associated approximation is explicitly quantified by the optimized relaxation variables and the residual norms reported in Section 5.1. Similar methods have also been adopted in [33, 34].

Remark 4. It is worth highlighting that, although the estimation errors are guaranteed to be uniformly ultimately bounded, asymptotic convergence to the origin is not assured. Nevertheless, according to [35], the ultimate estimation-error bounds can be reduced by appropriately selecting the design parameters. From (47), increasing ξ , while decreasing μ , N_0 , and β_0 , leads to smaller ultimate error bounds. Furthermore, according to the definition $\beta_0 = \frac{v_2}{v_1} \bar{f}^2 + \frac{1}{\alpha_0 v_1} \bar{f}^2 + cd_2 \bar{\psi}^2 + 2b_0$ in (35), the bound of the state-estimation error can be reduced by increasing v_1 and α_0 , and decreasing v_2 , cd_2 , and b_0 . In addition, increasing ε , $v_2 - \alpha_0$, and $cd_1 cd_2$ increases the decay rate β , which permits a larger ξ and consequently further reduces the ultimate error bound. For the actuator-fault estimation error, v_1 should be selected appropriately because it also appears explicitly in its ultimate bound in (47). Since

the adaptive gains depend sensitively on the plant parameters, their practical values should be determined through simulation, experimentation, and iterative adjustment [36].

Remark 5. The equality constraints in (21) and (22) are not convenient to impose directly by using the standard MATLAB LMI Toolbox. To make these conditions computationally tractable, a scalar relaxation variable $l_i > 0$ is introduced to describe the residual of the equality constraints. For compactness, define

$$\Xi_i = \begin{bmatrix} \bar{B}_{ai}^T \\ L_{\phi i}^T \end{bmatrix} (\bar{S}^{-1})^T P_i - \begin{bmatrix} R_{1i} \\ R_{2i} \end{bmatrix} \bar{C}. \quad (50)$$

Then, the original equality constraints can be handled by solving the following auxiliary LMI optimization problem:

$$\begin{aligned}\min \quad & l_i \\ \text{s.t.} \quad & \begin{bmatrix} -l_i I_3 & \Xi_i \\ * & -I_8 \end{bmatrix} < 0, \\ & P_i \bar{S}^{-1} \bar{A}_i + \bar{A}_i^T (\bar{S}^{-1})^T P_i - \bar{Y}_i \bar{C} - \bar{C}^T \bar{Y}_i^T + \varepsilon P_i < 0,\end{aligned}\quad (51)$$

where $\bar{Y}_i = P_i \bar{S}^{-1} L_{pi}$. After solving the above LMI problem, the observer gain can be recovered by

$$L_{pi} = \bar{S} P_i^{-1} \bar{Y}_i. \quad (52)$$

According to the Schur complement, the first inequality in (51) implies that the residual Ξ_i is bounded by the relaxation variable l_i . Hence, minimizing l_i reduces the residual associated with the exact equality constraints in (21) and (22). The optimized relaxation variable and the corresponding residual norm are therefore used to quantify the numerical deviation from these exact theoretical conditions.

5. Simulation Validation

5.1. Simulation Results of the Proposed Method

Numerical experiments presented here demonstrate the efficacy of the developed adaptive observer. The switched circuit model has been established in Section 2; hence, this section only presents the simulation settings, observer parameters, and numerical results.

The circuit parameters in (1) are selected as follows: $L_1 = 10 \text{ mH}$, $L_2 = 10 \text{ mH}$, $C_1 = 10 \text{ }\mu\text{F}$, $C_2 = 10 \text{ }\mu\text{F}$, $C_3 = 22 \text{ }\mu\text{F}$, $R_1 = 150 \text{ }\Omega$, $R_2 = 120 \text{ }\Omega$, and $R_3 = 300 \text{ }\Omega$. The faults, external disturbance, and control input are considered as

$$\begin{aligned}f_s(t) &= \sin(t), f_a(t) = 0.7 \cos(t), \\ d(t) &= \sin(5t), u_c(t) = 5.\end{aligned}$$

By using the LMI Toolbox in MATLAB and applying Theorem 1, the feasible observer gains and design matrices are obtained. The matrices P_i and L_{pi} , $i \in \gamma$, are listed as follows:

$$\begin{aligned}
P_1 &= \begin{bmatrix} 0.1819 & -0.0851 & -0.0146 & 0.0607 & 0.0220 & -0.0146 & 0.0587 & 0.0219 \\ -0.0851 & 0.1955 & -0.0019 & -0.0625 & 0.1044 & -0.0019 & -0.0607 & 0.1042 \\ -0.0146 & -0.0019 & 6.8445 & -0.2757 & -0.2221 & 6.8424 & -0.2774 & -0.2259 \\ 0.0607 & -0.0625 & -0.2757 & 8.4376 & -0.6291 & -0.2751 & 8.4368 & -0.6279 \\ 0.0220 & 0.1044 & -0.2221 & -0.6291 & 8.2131 & -0.2153 & -0.6227 & 8.2230 \\ -0.0146 & -0.0019 & 6.8424 & -0.2751 & -0.2153 & 6.8405 & -0.2768 & -0.2191 \\ 0.0587 & -0.0607 & -0.2774 & 8.4368 & -0.6227 & -0.2768 & 8.4363 & -0.6214 \\ 0.0219 & 0.1042 & -0.2259 & -0.6279 & 8.2230 & -0.2191 & -0.6214 & 8.2333 \end{bmatrix}, \\
P_2 &= \begin{bmatrix} 0.1729 & -0.0783 & -0.0163 & 0.0637 & 0.0424 & -0.0162 & 0.0618 & 0.0423 \\ -0.0783 & 0.1906 & -0.0008 & -0.0497 & 0.1007 & -0.0008 & -0.0479 & 0.1004 \\ -0.0163 & -0.0008 & 6.8967 & -0.1223 & -0.1519 & 6.8936 & -0.1249 & -0.1578 \\ 0.0637 & -0.0497 & -0.1223 & 8.6326 & -0.4460 & -0.1254 & 8.6282 & -0.4533 \\ 0.0424 & 0.1007 & -0.1519 & -0.4460 & 8.2875 & -0.1502 & -0.4449 & 8.2855 \\ -0.0162 & -0.0008 & 6.8936 & -0.1254 & -0.1502 & 6.8907 & -0.1280 & -0.1561 \\ 0.0618 & -0.0479 & -0.1249 & 8.6282 & -0.4449 & -0.1280 & 8.6240 & -0.4523 \\ 0.0423 & 0.1004 & -0.1578 & -0.4533 & 8.2855 & -0.1561 & -0.4523 & 8.2840 \end{bmatrix}, \\
L_{p1} &= 10^4 \times \begin{bmatrix} -0.0088 & 0.0035 & -0.0373 \\ 0.0052 & -0.0081 & 0.0213 \\ 3.2916 & 3.6551 & 6.1409 \\ 1.0036 & -0.7468 & 4.1921 \\ -0.5098 & 0.9808 & -0.6384 \\ -0.0007 & -0.0013 & -0.0023 \\ 0.0004 & 0.0007 & 0.0009 \\ 0.0028 & 0.0038 & 0.0075 \end{bmatrix}, L_{p2} = 10^4 \times \begin{bmatrix} 0.0001 & 0.0161 & -0.0224 \\ 0.0014 & -0.0130 & 0.0194 \\ 2.5500 & 2.1730 & 4.9528 \\ 0.0751 & -2.0548 & 2.9999 \\ -0.6096 & 0.4303 & -1.1225 \\ -0.0005 & -0.0005 & -0.0024 \\ -0.0004 & -0.0002 & -0.0020 \\ 0.0006 & 0.0002 & 0.0014 \end{bmatrix}. \quad (53)
\end{aligned}$$

The parameter ε is chosen as 1. The adaptive gains and auxiliary constants take the following values: $v_1 = 70,000$, $v_2 = 200$, $cd_1 = 5$, $cd_2 = 3$, $b_0 = 0.03$, $b_1 = 1$, and $\alpha_0 = 0.1$. According to Theorem 1, the resulting parameters are $\beta = 0.5$, $\mu = 1.5836$, and $\tau_a = 1$, which satisfies the ADT requirement $\tau_a > \tau_a^* = \frac{\ln \mu}{\beta} = 0.9194$. The observer is initialized with $\hat{x}(0) = [-0.1, -0.1, -1, 0.2, 1]^T$, while the initial estimates of the faults are chosen as $\hat{f}_s(0) = 0.8$ and $\hat{f}_a(0) = -0.6$.

The proposed observer is evaluated through a 20 s simulation under the ADT-based switching strategy. Figure 2 shows the switching signal $\varsigma(t)$, which satisfies the prescribed ADT requirement. Figure 3a–e display the state estimation results, and the fault estimation results are demonstrated in Figure 4a,b. The obtained results indicate that the developed observer achieves accurate tracking of the system states and the sensor fault $f_s(t)$. Although the estimation of the actuator fault $f_a(t)$ contains small switching-induced fluctuations, the estimation error remains bounded. These simulation findings demonstrate that the developed adaptive observer is effective.

The corresponding simulation estimation errors are depicted in Figure 5. Specifically, Figure 5a–e presents the state estimation errors $\hat{x}_i(t) - x_i(t)$, $i = 1, 2, \dots, 5$, while Figure 5f shows the sensor fault estimation error $\hat{f}_s(t) - f_s(t)$ and the actuator fault estimation error $\hat{f}_a(t) - f_a(t)$. The results indicate that the state estimation errors decrease rapidly after the initial transient and enter a small neighborhood of zero within approximately 0.35 s. After that, the state estimation errors remain within approximately 0.033. For the fault estimation errors, $\hat{f}_s(t) - f_s(t)$ and $\hat{f}_a(t) - f_a(t)$ enter small

neighborhoods of zero within approximately 0.55 s and 0.69 s, respectively. After convergence, the sensor fault estimation error remains within approximately 0.01, whereas the actuator fault estimation error remains within approximately 0.09. In addition, several short-time fluctuations can be observed around the switching instants.

Following the relaxation strategies adopted in [37,38], the matrix equality constraints are replaced by an auxiliary LMI optimization problem with positive scalar relaxation variables. To quantify the approximation introduced by the relaxed equality constraints, the obtained relaxation variables and residual norms are reported. For modes 1 and 2, the optimized relaxation variables are $l_1 = 5.4320 \times 10^{-3}$ and $l_2 = 5.5042 \times 10^{-3}$, respectively. The corresponding residuals satisfy $\|\Xi_1\|_2 = 7.2931 \times 10^{-2}$ and $\|\Xi_2\|_2 = 7.2526 \times 10^{-2}$. According to the Schur complement, the relaxed LMI implies $\Xi_i \Xi_i^T < l_i I$, and hence $\|\Xi_i\|_2 < \sqrt{l_i}$. In the present case, $\sqrt{l_1} = 7.3702 \times 10^{-2}$ and $\sqrt{l_2} = 7.4190 \times 10^{-2}$, confirming that the obtained residuals satisfy the prescribed relaxation bounds.

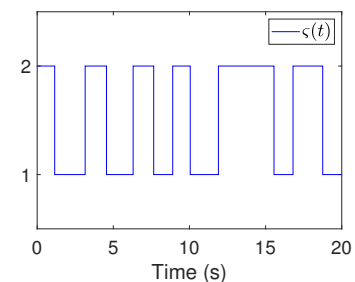


Figure 2. The switching signal $\varsigma(t)$ in the numerical simulation.

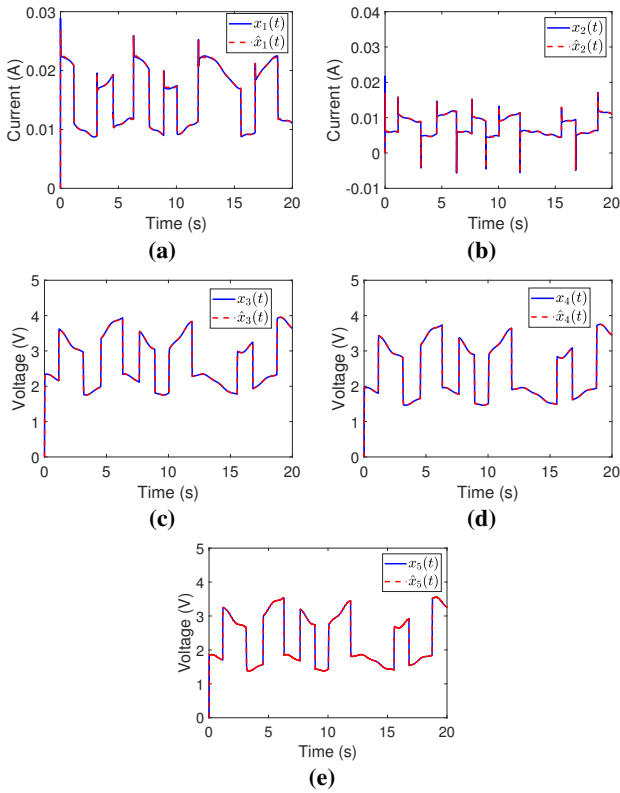


Figure 3. The state estimations. (a) State $x_1(t)$ and its estimation $\hat{x}_1(t)$. (b) State $x_2(t)$ and its estimation $\hat{x}_2(t)$. (c) State $x_3(t)$ and its estimation $\hat{x}_3(t)$. (d) State $x_4(t)$ and its estimation $\hat{x}_4(t)$. (e) State $x_5(t)$ and its estimation $\hat{x}_5(t)$.

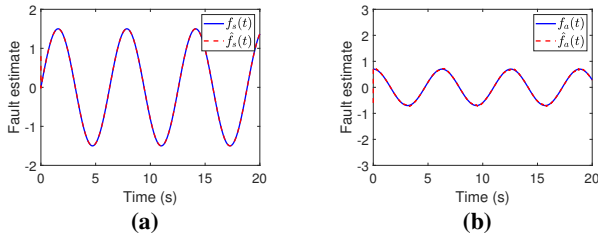


Figure 4. The fault estimations. (a) Sensor fault $f_s(t)$ and its estimation $\hat{f}_s(t)$. (b) Actuator fault $f_a(t)$ and its estimate $\hat{f}_a(t)$.

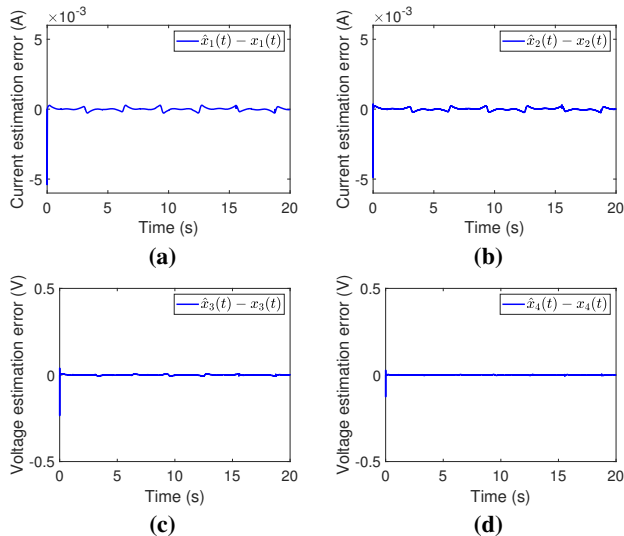


Figure 5. Cont.

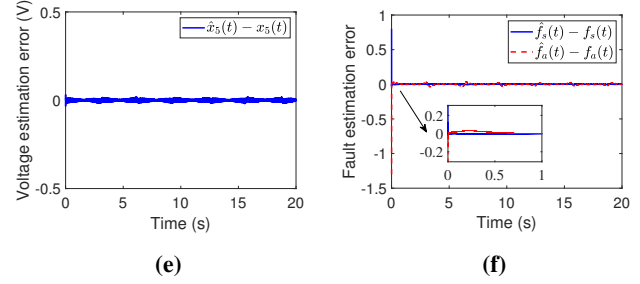


Figure 5. The simulation estimation errors. (a) Current-state estimation error $\hat{x}_1(t) - x_1(t)$. (b) Current-state estimation error $\hat{x}_2(t) - x_2(t)$. (c) Voltage-state estimation error $\hat{x}_3(t) - x_3(t)$. (d) Voltage-state estimation error $\hat{x}_4(t) - x_4(t)$. (e) Voltage-state estimation error $\hat{x}_5(t) - x_5(t)$. (f) Fault estimation errors. The inset is a blowup of the fault estimation errors within 0–1 s.

5.2. Comparative Simulation Results

To further demonstrate the effectiveness of the observer proposed in this paper, the sensor fault estimation error of the proposed method is compared with that obtained using the augmented-state observer in [39], while the actuator fault estimation error is compared with that obtained using the high-order unknown input observer (HOUIO) in [40].

For comparison with the proposed sensor fault estimation scheme, the method in [39] is implemented, in which the sensor fault is treated as an auxiliary state and estimated together with the system states through an augmented-state observer. Following [39], the design parameters are selected as $(\mu_1, \mu_2) = (3, 4)$, $(\lambda_1, \lambda_2) = (12, 8)$, and $(\Upsilon_1, \Upsilon_2) = (20, 20)$. The comparison of the sensor fault estimation errors is presented in Figure 6a. For $t \geq 1$ s, the maximum absolute estimation error of the proposed method is approximately 0.0015, while that of the method in [39] is approximately 0.0391. Therefore, the proposed observer achieves higher sensor fault estimation accuracy.

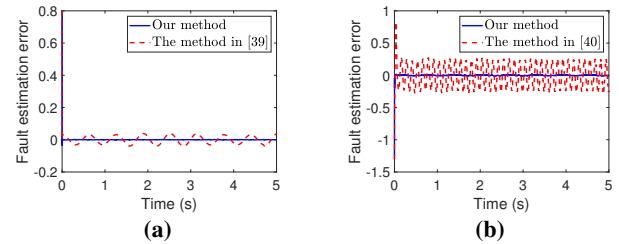


Figure 6. Comparison of fault estimation errors. (a) Sensor fault estimation errors of the proposed method and the method in [39]. (b) Actuator fault estimation errors of the proposed method and the method in [40].

Furthermore, following [40], the HOUIO is implemented for actuator fault estimation. In the high-order sliding-mode differentiator, the parameters are selected as $\rho = 3000$, $\lambda_0 = 1.1$, and $\lambda_1 = 2$. The actuator fault is reconstructed according to

$$\hat{f}_a(t) = (CE_i)^+ [\hat{y}_v(t) - C(A_i - L_i C)\hat{v}(t)].$$

The actuator fault estimation error comparison is shown in Figure 6b. After the initial transient, i.e., for $t \geq 1$ s, the maximum absolute estimation error of the proposed method is approximately 0.0088, whereas that of the method in [40] reaches approximately 0.3743. Therefore, the proposed observer provides higher actuator fault estimation accuracy.

Remark 6. For the considered circuit system, the theoretical ADT bound obtained from Theorem 1 is $\tau_a^* = \ln(\mu)/\beta = 0.9194$ s. Therefore, the uniform ultimate boundedness of the estimation errors is guaranteed for switching signals satisfying $\tau_a > \tau_a^*$. This relatively small lower bound indicates that the proposed observer can accommodate relatively frequent switching operations. As the switching becomes faster, τ_a decreases. As long as the ADT condition is still satisfied, the stability conclusion of Theorem 1 remains valid. If τ_a falls below the theoretical bound, the present theorem no longer guarantees the uniform ultimate boundedness of the estimation errors. However, the derived ADT condition is sufficient rather than necessary. Therefore, violation of this bound does not necessarily imply instability. Nevertheless, the estimation performance may deteriorate under excessively fast switching.

6. Validation on a Practical Circuit Platform

The proposed theoretical framework is further implemented on a practical circuit platform, as shown in Figure 7. The experimental circuit is built following the configuration illustrated by Figure 1, with component values matching those adopted for numerical simulation. Consequently, the numerical and experimental findings share a common system model, thereby providing cross-verification of the effectiveness of the developed observer.

The circuit is fabricated on a printed circuit board (PCB), and an external 3–15 V adjustable DC power supply module, HU-M14C, is used as the input source. The resistors, capacitors, and inductors adopted in the experimental circuit are selected according to the same parameter settings as those in the simulation. Moreover, a voltage regulation circuit based on a TLC272CP operational amplifier, a BC337-25 transistor, and a voltage follower is employed to emulate the external disturbance $d(t)$.

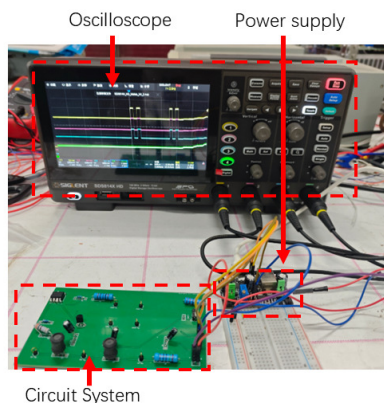


Figure 7. The experimental circuit platform.

A four-channel digital oscilloscope is used for data acquisition, with the power supply signal and the three capacitor voltages $v_1(t)$, $v_2(t)$, and $v_3(t)$ recorded simultaneously. In the mathematical model, these voltage signals correspond to the states $x_3(t)$, $x_4(t)$, and $x_5(t)$, respectively. Owing to the relatively small amplitudes of the current signals in the experimental circuit, reliable reference current measurements cannot be obtained using the present measurement configuration. Therefore, the current variables $x_1(t)$ and $x_2(t)$ are treated as unmeasurable states and reconstructed by the proposed observer, with the reconstructed trajectories shown in Figure 8. It should be noted that the proposed observer requires only the three capacitor voltages $v_1(t)$, $v_2(t)$, and $v_3(t)$ as measurable outputs. Thus, the absence of direct current measurements does not affect the implementation of the proposed fault estimation scheme. However, since no independent hardware reference is available for the current states, the estimation accuracy of $x_1^*(t)$ and $x_2^*(t)$ cannot be quantitatively evaluated through direct experimental measurements. Accordingly, Figure 8 is intended to present the current trajectories reconstructed by the observer rather than to provide a direct experimental validation of their estimation accuracy.

Although the proposed observer is formulated in continuous time, its numerical and experimental implementations are performed using sampled data. In the present implementation, the sampling interval is approximately $T_s = 10^{-4}$ s, corresponding to approximately 250,000 sampling points over a 25 s interval. At each sampling instant, the observer states and fault estimates are recursively updated using the current measurement and the previously obtained observer variables. Therefore, the small sampling interval provides a high-resolution numerical approximation of the continuous-time observer dynamics.

The switching signal is configured with the average dwell-time parameter $\tau_a = 1$, satisfying the prescribed ADT constraint $\tau_a \geq \tau_a^*$.

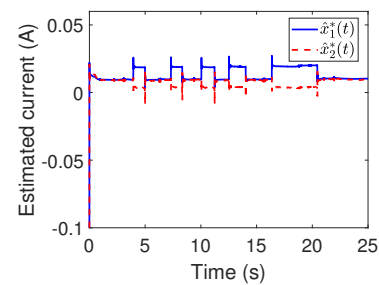


Figure 8. The observer-reconstructed current states $\hat{x}_1^*(t)$ and $\hat{x}_2^*(t)$ without direct current reference measurements.

The proposed design, implemented on the practical circuit platform under the ADT-based switching strategy, is evaluated through a 25 s experimental test. To distinguish the experimental signals from those used in the simulation study, the superscript “*” is adopted throughout this subsection. Specifically, $\varsigma^*(t)$ denotes the experimentally implemented switching signal, $x_i^*(t)$ and $\hat{x}_i^*(t)$ denote the experimental state and its

corresponding estimate, respectively. $f_s^*(t)$ and $f_a^*(t)$ denote the prescribed sensor-fault signal and the physically introduced actuator-fault reference, respectively, while $\hat{f}_s^*(t)$ and $\hat{f}_a^*(t)$ denote their corresponding estimates.

The experimental results obtained from the practical circuit platform are presented in Figures 9–12. Figure 9 shows the switching signal $\varsigma^*(t)$ recorded from the experimental platform, where the switching behavior satisfies the prescribed ADT requirement. The proposed observer is implemented using the measured voltage states $x_3^*(t)$, $x_4^*(t)$, and $x_5^*(t)$, with the corresponding measured and estimated trajectories presented in Figure 10a–c. It can be observed that $\hat{x}_3^*(t)$, $\hat{x}_4^*(t)$, and $\hat{x}_5^*(t)$ can effectively track $x_3^*(t)$, $x_4^*(t)$, and $x_5^*(t)$, respectively, even under the switching operation. Moreover, the estimation results of faults are given in Figure 11a–b, where the corresponding estimates $\hat{f}_s^*(t)$ and $\hat{f}_a^*(t)$ show satisfactory tracking performance.

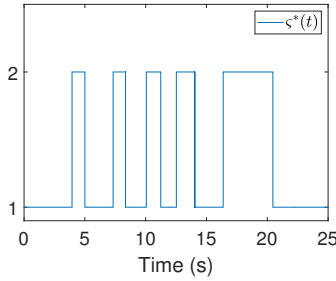


Figure 9. The experimental switching signal $\varsigma^*(t)$.

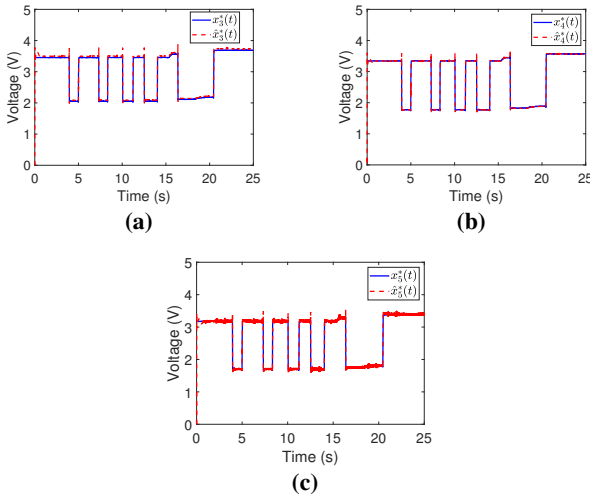


Figure 10. The experimental state estimations. (a) State $x_3^*(t)$ and its estimation $\hat{x}_3^*(t)$. (b) State $x_4^*(t)$ and its estimation $\hat{x}_4^*(t)$. (c) State $x_5^*(t)$ and its estimation $\hat{x}_5^*(t)$.

The corresponding experimental estimation errors are shown in Figure 12. Specifically, Figure 12a–c presents the voltage-state estimation errors $\hat{x}_k^*(t) - x_k^*(t)$, $k = 3, 4, 5$, while Figure 12d shows the actuator fault estimation error $\hat{f}_a^*(t) - f_a^*(t)$ and the sensor fault estimation error $\hat{f}_s^*(t) - f_s^*(t)$. Due to the mismatch between the initial observer states and the actual initial states of the practical circuit, estimation errors appear at the initial stage of the experiment. However, as the system operates, the estimation errors decrease rapidly. As shown in Figure 12a–c, the state tracking errors enter a

small neighborhood of zero within approximately 0.7 s and remain within approximately 0.039. Moreover, as shown in Figure 12d, both $\hat{f}_s^*(t) - f_s^*(t)$ and $\hat{f}_a^*(t) - f_a^*(t)$ enter small neighborhoods of zero within approximately 0.8 s. After that, the sensor fault estimation error remains within approximately 0.038, while the actuator fault estimation error remains within approximately 0.028. In addition, several short-time error peaks can be observed at the switching instants. After the initial transient, the peak magnitudes of the state estimation errors in Figure 12a–c do not exceed 0.51. For the fault estimation errors in Figure 12d, the absolute peak value of $\hat{f}_s^*(t) - f_s^*(t)$ remains below 0.42, whereas that of $\hat{f}_a^*(t) - f_a^*(t)$ is less than 0.064. These transient peaks are mainly associated with system switching and practical measurement fluctuations. For each switching event, the errors decay quickly and return to a small neighborhood of zero. Throughout the whole experimental process, the estimation errors remain bounded, further confirming that the developed observer performs effectively under voltage-output measurement conditions.

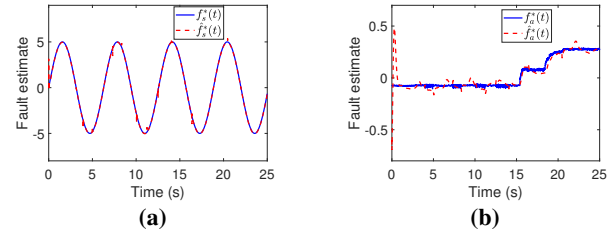


Figure 11. The experimental fault estimations. (a) Sensor fault $f_s^*(t)$ and its estimation $\hat{f}_s^*(t)$. (b) Actuator fault $f_a^*(t)$ and its estimation $\hat{f}_a^*(t)$.

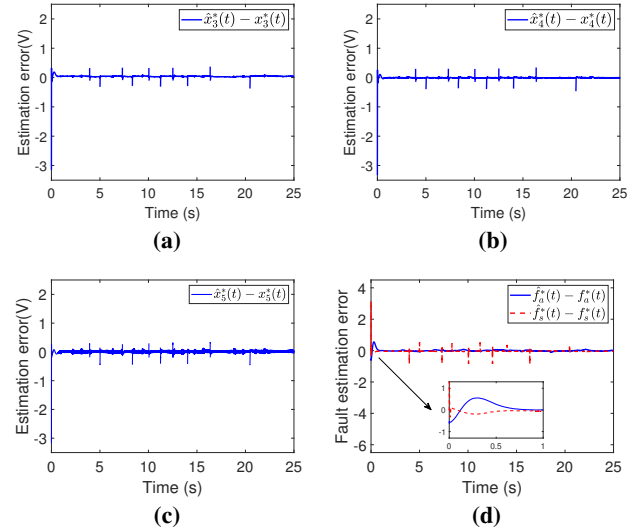


Figure 12. The experimental estimation errors. (a) Voltage-state estimation error $\hat{x}_3^*(t) - x_3^*(t)$. (b) Voltage-state estimation error $\hat{x}_4^*(t) - x_4^*(t)$. (c) Voltage-state estimation error $\hat{x}_5^*(t) - x_5^*(t)$. (d) Fault estimation errors. The inset is a blowup of the fault estimation errors within 0–1 s.

To further quantify the experimental estimation performance, the root-mean-square error (RMSE) values and peak estimation errors are calculated for the measurable voltage

states and fault signals, as summarized in Table 1. The results show that the RMSE values of all estimated variables remain below 0.06, indicating satisfactory estimation accuracy under practical experimental conditions.

Table 1. Quantitative evaluation of the experimental estimation errors

Variable	RMSE	Peak Error
$\hat{x}_3^*(t) - x_3^*(t)$	0.043314	0.40551
$\hat{x}_4^*(t) - x_4^*(t)$	0.016345	0.50477
$\hat{x}_5^*(t) - x_5^*(t)$	0.040510	0.52911
$\hat{f}_a^*(t) - f_a^*(t)$	0.030777	0.0637
$\hat{f}_s^*(t) - f_s^*(t)$	0.043366	0.41356

Owing to the relatively small amplitudes of the current signals in the experimental circuit, reliable reference current measurements cannot be obtained using the present measurement configuration. Therefore, the current states shown in Figure 8 are observer-reconstructed states rather than current trajectories independently verified by direct measurements. It should be noted that the proposed observer requires only the three capacitor voltages $v_1(t)$, $v_2(t)$, and $v_3(t)$ as measurable outputs. Therefore, the absence of direct current measurements does not affect the implementation of the proposed fault estimation scheme.

Remark 7. The actuator fault, sensor fault, and external disturbance are introduced using different mechanisms in the experimental validation. The actuator fault is physically introduced by adjusting the HU-M14C DC power-supply module. With the nominal input voltage selected as 5 V, the actuator-fault reference is defined as

$$f_a^*(t) = u_{in}^*(t) - 5, \quad (54)$$

where $u_{in}^*(t)$ denotes the actual input voltage measured during the experiment. The input voltage and the three capacitor voltages $v_1^*(t)$, $v_2^*(t)$, and $v_3^*(t)$ are simultaneously acquired using a four-channel digital oscilloscope and therefore share the same sampling clock and time base. In contrast, the sensor fault is digitally injected into the experimentally acquired output according to

$$y^*(t) = Cx^*(t) + D_s f_s^*(t), \quad (55)$$

where $f_s^*(t)$ is a prescribed sensor-fault signal and is therefore exactly known. The external disturbance $d(t)$ is physically emulated using a voltage regulation circuit consisting of a TLC272CP operational amplifier, a BC337-25 transistor, and a voltage follower.

The measured voltage sequence and the prescribed sensor-fault sequence are indexed at the same sampling instants, ensuring their temporal synchronization. At each sampling instant, the observer uses only the current measurement and the previously updated observer variables to calculate the

current state and fault estimates. Therefore, no future measurement information is involved, and the fault estimates are synchronized with the corresponding injected fault signals.

Remark 8. It should be noted that several unavoidable uncertainties exist in the practical experiment. The voltage signals acquired by the digital oscilloscope are inevitably affected by measurement errors and electrical noise. In addition, the nonideal characteristics of the physical switch may introduce transient perturbations around the switching instants. Parameter uncertainties also arise from component tolerances: the resistors, capacitors, and inductors have allowable tolerances of approximately $\pm 1\%$, $\pm 20\%$, and $\pm 10\%$, respectively. Moreover, the practical inductors introduce an equivalent series resistance of approximately $4\ \Omega$, which is not included in the nominal model. Therefore, the experimental results inherently reflect the influence of measurement uncertainty, switching nonidealities, parameter perturbations, and unmodeled parasitic effects. It is worth noting that the designed injection term $u_\phi(t)$ in (14) can, to some extent, attenuate random external disturbances arising during oscilloscope measurements.

7. Conclusions

The present work investigated joint estimation of system states and fault signals in switched circuit models subject to actuation-channel faults, sensor faults, and exogenous perturbations under an average dwell-time (ADT) switching law. A switched circuit model was first established to characterize the mode-dependent circuit dynamics and the effects of different fault signals. By incorporating the sensor-fault-related term into an augmented descriptor representation, a multimode adaptive observer was developed to reconstruct the system states, actuator fault, and sensor fault simultaneously. By employing a mode-dependent Lyapunov function together with the ADT switching technique, sufficient criteria were established to ensure uniform ultimate boundedness of the resulting estimation errors. Both numerical studies and physical experiments conducted on a switched circuit platform further demonstrated the efficacy of the developed approach. The obtained findings indicate that the developed observer can effectively track the system states and fault signals under switching operations and external disturbances. Moreover, the experimental results demonstrate the estimation performance for the directly measurable voltage states and fault signals, while the unmeasurable current states are reconstructed by the observer using only the voltage signals as measured outputs.

Author Contributions

X.K.: writing—original draft, investigation; Y.T.: writing—review and editing, supervision, project administration, methodology; L.C.: validation. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement

Not applicable.

Data Availability Statement

Data are contained within the article.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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