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Cyber Security of Water SCADA Systems—Part II: Attack Detection Using Enhanced Hydrodynamic Models

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***Abstract*— This paper investigates the problem of detection and isolation of attacks on a water distribution network comprised of cascaded canal pools. The proposed approach employs a bank of delay-differential observer systems. The observers are based on an analytically approximate model of canal hydrodynamics. Each observer is insensitive to one fault/attack mode and sensitive to other modes. The design of the observers is achieved by using a delay-dependent linear matrix inequality method. The performance of our model-based diagnostic scheme is tested on a class of adversarial scenarios based on a generalized fault/attack model. This model represents both classical sensor-actuator faults and communication network-induced deception attacks. Our particular focus is on stealthy deception attacks in which the attacker's goal is to pilfer water through canal offtakes. Our analysis reveals the benefits of accurate hydrodynamic models in detecting physical faults and cyber attacks to automated canal systems. We also comment on the criticality of sensor measurements for the purpose of detection. Finally, we discuss the knowledge and effort required for a successful deception attack.**

***Index Terms*— Delay systems, fault diagnosis, intrusion detection, supervisory control and data acquisition (SCADA) systems, supervisory control.**

I. Introduction

MODERNIZATION of irrigation canal systems is often viewed as a solution for improving their operational performance. In many countries, networked and fully gated irrigation systems have been instrumented with supervisory control and data acquisition (SCADA) systems to enable communications, sensing, and control. Real-time knowledge of the system state and the ability to remotely control flows at critical points can vastly improve the performance of irrigation systems [1], [2]. To sustain modernization plans of irrigation systems, a legislative framework and well-defined rules for demand regulation and maintenance are being developed. Today, numerous automatic control methods are available for regulating water flow in canal systems; see [3] and [4] for a survey of these methods.

However, modernization does not always imply reliable service [5]. Even in developed countries, automated irrigation systems are experiencing significant levels of water loss due to management and distribution related inefficiencies. These issues become more challenging for developing countries. Clemmens [6] has argued that reduced water flows and large deviations from target levels at downstream ends can lead to inefficient water distribution. This can incentivize the end users to tamper with canal system operations. For example, the farmers at downstream ends may have incentives to steal water and not pay for its use. In addition to the existing issues of random faults and unauthorized withdrawals, an increased reliance on open communication networks to transmit and receive control data has added new concerns of cyber attacks [7]–[9].

In [10], we highlighted the ways in which simultaneous and uncoupled cyber-physical faults (or cyber attacks) in automated irrigation canal systems can be achieved by an intelligent adversary. By presenting the results from a field operational test, we showed that it is possible for an attacker to withdraw water from an automated canal without getting detected. This motivates the need of better fault/attack detection mechanisms based on sound hydrodynamic principles. In this article, we introduce a generalized fault/attack model that permits us to consider both random sensor-actuator faults and a class of cyber attacks. We focus on the design of a fault/attack detection and isolation (F/ADI) scheme based on accurate hydrodynamic models. In our design, we use recent theoretical results [11]–[14] on observer design for time-delay systems in the presence of unknown inputs.

A wide body of work already exists on the problem of fault detection and isolation (FDI) of unknown withdrawals (or leaks) [15], [16], and random sensor-actuator faults in canal systems [17]. The authors in [17] use data reconciliation based on static and dynamic models to isolate unknown withdrawals and random faults. A simple finite-dimensional model of canal

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flow is used in [16] to generate residuals between the model and observed data. The residuals are aggregated over time by a cumulative sum (CUSUM) algorithm (based on the theory of change-point detection [18]). An alert for a leak is generated when the CUSUM statistic reaches a given threshold. Under the assumption that the size of the leak and the time of start are known, [15] uses a bank of Luenberger observers based on the shallow water equations to localize the leaks. The authors of [15] also discuss the use of observed time-difference between the effect of leaks seen at the upstream and downstream of canal pools to localize the leaks. Results on stability of hyperbolic conservation laws [19], [20] are used to prove observer stability in [15]. Response mechanisms to address random faults are presented in [21].

The most closely related works to this paper are [11] and [22]. This paper [22] provides a comparison of different methods of residual generation based on finite- and infinite-dimensional models. The authors propose that a properly tuned CUSUM algorithm can achieve leak detection. An estimate of water leakage is generated from residuals based on a simple conversion formula. A technique to isolate a single sensor fault from a single leak is presented based on monitoring of canal pools located upstream and downstream of the suspect pool. This paper [11] uses unknown input observers (UIO) for time-delay systems (e.g., [12] and [13]) to design a FDI scheme for a single canal reach. This approach was extended to multiple pools when only downstream levels are measured in [23].

The problem of isolating sensor-actuator faults from unknown water withdrawals is difficult because both these faults have similar effects on the observer residuals. Moreover, to the best of our knowledge, the performance of available diagnostic schemes where sensor-actuator faults and unknown water withdrawals occur simultaneously has not been investigated in the literature. From the viewpoint of security of automated canal systems, such simultaneous faults form an interesting class of attacks. Indeed, an intelligent attacker, who is interested in water pilfering or has malicious intentions to harm canal operations, can conduct such attacks [10]. In this article, we further analyze such attacks.

The main contributions of this paper are as follows.

1) We present conditions for detectability and isolability of faults due to nonsimultaneous (and uncoupled) withdrawals and sensor disturbances in cascade of canal pools. Our UIO design uses an analytic approximation of the canal hydrodynamics (Theorem 2). This model captures the effect of both upstream and downstream flow variations. The diagnostic scheme can be designed provided that a feasible solution to delay-dependent observer stability criterion exists (Proposition 3), and observer decoupling conditions are satisfied (Definition 1).
2) We propose a F/ADI (diagnostic) scheme based on the bank of UIOs, and analyze its performance under simultaneous and uncoupled faults (called attacks). Specifically, we consider simultaneous compromise of one or more sensor measurements and water pilfering using offtake structures. We discuss the implications of our findings on the security of water SCADA systems. More generally, our analysis points toward fundamental limitations of model-based diagnostic schemes in isolating attacks to distributed physical infrastructures.

This paper is organized as follows. In Section II, we first introduce infinite-dimensional models for a cascade of canal pools, and describe an analytically approximate finite-dimensional model. This model is used to design a UIO-based scheme for detecting faults entering in state and measurement equations in Section III. In Section IV, we present a generalized fault/attack model which captures attack scenarios, such as simultaneous water pilfering through offtakes and sensor compromise. Next, we analyze the advantages and limitations of the proposed diagnostic scheme. We also discuss security implications of typical attack scenarios resulting from our generalized fault/attack model. Concluding remarks are drawn in Section V.

II. Models of Canal Pool Cascade

A. Model of Flow Dynamics

Consider an irrigation system consisting of a cascade of m canal pools. Each pool is represented by a portion of canal in between two automated hydraulic structures. We assume that pool i, where $i = 1, \dots, m$ has a prismatic cross section and is of length l_i (m). Let the space variable be denoted by $x \in [0, l_i]$ and time variable by $t \in \mathbb{R}_+$. The unsteady flow dynamics of each canal pool are classically modeled by the 1-D shallow water equations (SWE) [4]. The SWEs are coupled hyperbolic PDEs with $\mathrm{A}_i(t,x)$ the wetted cross-sectional area (m^2), and $\mathrm{Q}_i(t,x)$ the discharge (m^3/s) across cross section A_i as the dependent variables, and t and x as independent variables. The SWE for pool i is given by

$$\partial_t \begin{pmatrix} \mathrm{A}_i \\ \mathrm{Q}_i \end{pmatrix} + \mathbf{F}(\mathrm{A}_i, \mathrm{Q}_i)\partial_x \begin{pmatrix} \mathrm{A}_i \\ \mathrm{Q}_i \end{pmatrix} = \mathbf{H}(\mathrm{A}_i, \mathrm{Q}_i) \tag{1}$$

on the domain $x \in (0, l_i),\ t > 0$ with

$$\mathbf{F}(\mathrm{A}_i, \mathrm{Q}_i) = \begin{pmatrix} 0 & 1 \\ g\mathrm{A}_i \partial_{\mathrm{A}_i} \mathrm{Y}_i(\mathrm{A}_i) - \frac{\mathrm{Q}_i^2}{\mathrm{A}_i^2} & 2\frac{\mathrm{Q}_i}{\mathrm{A}_i} \end{pmatrix}$$

$$\mathbf{H}(\mathrm{A}_i, \mathrm{Q}_i) = \begin{pmatrix} 0 \\ g\mathrm{A}_i(\mathrm{S}_{bi} - \mathrm{S}_{fi}(\mathrm{A}_i, \mathrm{Q}_i)) \end{pmatrix}.$$

Here the notation ∂_t, ∂_x, and ∂_{A_i} denote the partial derivatives with respect to t, x, and A_i, respectively. The function $\mathrm{S}_{fi}(\mathrm{A}_i, \mathrm{Q}_i)$ denotes the friction slope (m/m), S_{bi} the bed slope (m/m), $\mathrm{Y}_i(\mathrm{A}_i)$ the water depth (m) in section A_i, and g the acceleration due to gravity (m^2/s). We model the friction slope as $\mathrm{S}_{fi} := (\mathrm{Q}_i^2 n_i^2 / \mathrm{A}_i^2 R_i(\mathrm{A}_i)^{4/3})$, where n_i is the Manning roughness coefficient (sm$^{-1/3}$), $R_i(\mathrm{A}_i) := (P_i/\mathrm{A}_i)$ is the hydraulic radius (m), P_i is the wetted perimeter (m), $\mathrm{V}_i(t,x) := (\mathrm{Q}_i(t,x)/\mathrm{A}_i(t,x))$ is the average velocity (m/s) in section A_i, $\mathrm{C}_i(t,x) := \sqrt{(g\mathrm{A}_i(t,x)/\mathrm{T}_i(t,x))}$ is the celerity (m/s), and T_i is the top width (m).

We assume that $\mathrm{V}_i < \mathrm{C}_i$ (sub-critical flow), and therefore, one boundary condition must be specified at each boundary. The initial and boundary conditions are given by

$$\mathrm{Q}_i(t,0) = \mathrm{Q}_i^u(t) \quad \mathrm{Q}_i(t,l_i) = \mathrm{Q}_i^d(t) + \mathrm{P}_i(t), \qquad t \geqslant 0 \tag{2}$$

$$\mathrm{A}_i(0,x) = \mathrm{A}_{0,i}(x) \quad \mathrm{Q}_i(0,x) = \mathrm{Q}_{0,i}(x), \qquad x \in (0, l_i). \tag{3}$$

Here $\mathrm{Q}_i^u(t)$ and $\mathrm{Q}_i^d(t)$ denote the controllable upstream and downstream boundary discharges (m^3/s) for pool i, respectively, and $\mathrm{P}_i(t)$ denote the withdrawals through lateral offtakes (m^3/s). The boundary discharges are constrained as

$$\mathrm{Q}_i^d(t) = \mathrm{Q}_{i+1}^u(t), \qquad t \geqslant 0 \quad i = 0, \ldots, m. \tag{4}$$

We also assume the following: 1) the effect of offtakes along the canal pool can be lumped into a single perturbation $\mathrm{P}_i(t)$ acting near the downstream end of the pool;[1] 2) the conversion of the boundary discharges into automated movement of hydraulic structures is handled by the respective controllers located at these structures; and 3) the boundary discharges $\mathrm{Q}_i^u(t)$ and $\mathrm{Q}_i^d(t)$ are control variables, the offtake withdrawals $\mathrm{P}_i(t)$ are disturbance variables, and the levels $\mathrm{Y}_i(t, 0)$ and $\mathrm{Y}_i(t, l_i)$ [i.e., the areas $\mathrm{A}_i(t, 0)$ and $\mathrm{A}_i(t, l_i)$] are measured variables.

Overflow weirs and underflow gates are the most commonly used hydraulic structures for regulating canal networks. These structures can be in free-flow or submerged condition. In submerged condition (respectively, free-flow condition), the downstream level influences (respectively, does not influence) the flow through the structure. We define $\mathrm{Y}_0(t, l_0) := \mathrm{Y}_{\mathrm{up}}(t)$ and $\mathrm{Y}_{m+1}(t, 0) := \mathrm{Y}_{\mathrm{do}}(t)$, where $\mathrm{Y}_{\mathrm{up}}(t)$ (respectively, $\mathrm{Y}_{\mathrm{do}}(t)$) is the upstream (respectively, downstream) water levels of the first (respectively, last) canal pool in the cascade. The flow through structure i is modeled by a static nonlinear relation $\mathbf{G}_i$ with following general form (see [4, Sec VI.B])

$$\mathrm{Q}_i(t, l_i) = \mathbf{G}_i(\mathrm{Y}_i(t, l_i), \mathrm{Y}_{i+1}(t, 0), \mathrm{U}_i(t)) \tag{5}$$

for $i = 0, \ldots, m$, where $\mathrm{U}_i(t)$ denotes opening of the structure (m) at time t.

B. Linearized Models

Under compatible and constant openings $\mathrm{U}_i(t) = \bar{\mathrm{U}}_i$, withdrawals $\mathrm{P}_i(t) = \bar{\mathrm{P}}_i$, and levels $\mathrm{Y}_{\mathrm{up}}(t) = \bar{\mathrm{Y}}_{\mathrm{up}}$, $\mathrm{Y}_{\mathrm{do}}(t) = \bar{\mathrm{Y}}_{\mathrm{do}}$, (1)–(4) achieves a steady state. Let the wetted area and discharge in steady state be denoted by $\bar{\mathrm{A}}_i(x)$ and $\bar{\mathrm{Q}}_i(x)$, respectively, similarly for other variables. We henceforth omit the dependence on x. Following [4], SWE (1) can be linearized around a steady state $(\bar{\mathrm{A}}_i, \bar{\mathrm{Q}}_i)$. Let $\mathrm{a}_i(t, x) := (\mathrm{A}_i(t, x) - \bar{\mathrm{A}}_i(x))$, $\mathrm{q}_i(t, x) := (\mathrm{Q}_i(t, x) - \bar{\mathrm{Q}}_i(x))$ be the deviations from the steady state. The linearized SWE are given by

$$\frac{\partial}{\partial t}\begin{pmatrix}\mathrm{a}_i\\ \mathrm{q}_i\end{pmatrix} + \overline{\mathbf{F}}_i(x)\frac{\partial}{\partial x}\begin{pmatrix}\mathrm{a}_i\\ \mathrm{q}_i\end{pmatrix} + \overline{\mathbf{G}}_i(x)\begin{pmatrix}\mathrm{a}_i\\ \mathrm{q}_i\end{pmatrix} = 0 \tag{6}$$

on the domain $x \in (0, l_i), t \geqslant 0$, where $\left(\mathrm{a}_i(t, x),\ \mathrm{q}_i(t, x)\right)^{\mathsf{T}}$ is the state of canal pool i, and

$$\overline{\mathbf{F}}_i(x) := \begin{pmatrix}0 & 1\\ \alpha_i(x)\beta_i(x) & \alpha_i(x) - \beta_i(x)\end{pmatrix}$$
$$\overline{\mathbf{G}}_i(x) := \begin{pmatrix}0 & 0\\ -\gamma_i(x) & \delta_i(x)\end{pmatrix}.$$

Omitting the dependence on x, and defining $\kappa_i := (7/3) - (4\bar{\mathrm{A}}_i/3\bar{\mathrm{T}}_i\bar{P}_i)(\partial\bar{P}_i/\partial\bar{\mathrm{Y}}_i)$, we have $\alpha_i = \bar{\mathrm{C}}_i + \bar{\mathrm{V}}_i$, $\beta_i = \bar{\mathrm{C}}_i - \bar{\mathrm{V}}_i$, $\delta_i = (2g/\bar{\mathrm{V}}_i)\left(\bar{\mathrm{S}}_{fi} - (\bar{\mathrm{V}}_i^2\bar{\mathrm{T}}_i/g\bar{\mathrm{A}}_i)(d\bar{\mathrm{Y}}_i/dx)\right)$, and $\gamma_i = (\bar{\mathrm{C}}_i^2/\bar{\mathrm{T}}_i)(d\bar{\mathrm{T}}_i/dx) + g[(1+\kappa_i)\mathrm{S}_{bi} - (1 + \kappa_i - (\kappa_i - 2)(\bar{\mathrm{V}}_i^2\bar{\mathrm{T}}_i/g\bar{\mathrm{A}}_i)(d\bar{\mathrm{Y}}_i/dx)]$. System (6), along with the initial and boundary conditions

$$\mathrm{a}_i(0, x) = \mathrm{a}_{0,i}(x) \text{ and } \mathrm{q}_i(0, x) = \mathrm{q}_{0,i}(x), \qquad x \in (0, l_i) \tag{7}$$
$$\mathrm{q}_i(t, 0) = \mathrm{q}_i^u(t) \text{ and } \mathrm{q}_i(t, l_i) = \mathrm{q}_i^d(t) + \mathrm{p}_i(t), \qquad t \geqslant 0 \tag{8}$$

and the constraint

$$\mathrm{q}_i^d(t) = \mathrm{q}_{i+1}^u(t), \qquad t \geqslant 0 \tag{9}$$

form the linearized model for canal pool i, where $\mathrm{q}_i^u(t) = \mathrm{Q}_i(t, 0) - \bar{\mathrm{Q}}_i(0)$ and $\mathrm{q}_i^d(t) = \mathrm{Q}_i(t, l_i) - \bar{\mathrm{Q}}_i(l_i)$ denote the boundary discharge deviations, and $\mathrm{p}_i(t) = \mathrm{P}_i(t) - \bar{\mathrm{P}}_i$ the withdrawal deviations from the respective steady states. We note that for rectangular cross sections, the linearized model with $\mathrm{y}_i(t, x)$ and $\mathrm{a}_i(t, x)$ as state can be deduced by using

$$\mathrm{a}_i(t, x) = \bar{\mathrm{T}}(x)\mathrm{y}_i(t, x).$$

With a slight abuse of notation, we define (see Fig. 1)

$$\mathrm{q}_{i-1}(t) := \mathrm{q}_i^u(t) \quad \mathrm{q}_i(t) := \mathrm{q}_i^d(t)$$
$$\mathrm{y}_i^u(t) := \mathrm{y}_i(t, 0) \quad \mathrm{y}_i^d(t) := \mathrm{y}_i(t, l_i). \tag{10}$$

Finally, linearizing (5) about the steady state we obtain

$$\mathrm{q}_i(t) = b_i^d\mathrm{y}_i^d(t) + b_{i+1}^u\mathrm{y}_{i+1}^u(t) + k_i\mathrm{u}_i(t) \tag{11}$$

where $\mathrm{u}_i(t) = (\mathrm{U}_i(t) - \bar{\mathrm{U}}_i)$ denotes the deviation in the structure opening, the coefficients $b_i^d = (\overline{\partial_{\mathrm{Y}_i}\mathbf{G}_i})$ and $b_{i+1}^u = (\overline{\partial_{\mathrm{Y}_{i+1}}\mathbf{G}_i})$ are the feedback gains of upstream and downstream levels, and $k_i = (\overline{\partial_{\mathrm{U}_i}\mathbf{G}_i})$ is the gain of structure opening. Note that b_{i+1}^u is strictly negative (respectively, zero) for submerged (respectively, free-flow) condition, and b_i^d, k_i are positive.

C. Integrator-Delay (ID) Model

Using analytic approximation in the frequency domain, Litrico and Fromion have derived a finite-dimensional input–output model, which accounts for the effect of both upstream and downstream variations (see also [4, Sec. V.C]). In low-frequencies, this approximation is given by the ID model[2]

$$\begin{pmatrix}\hat{\mathrm{y}}_i^u(s)\\ \hat{\mathrm{y}}_i^d(s)\end{pmatrix} = \begin{pmatrix}\frac{a_i^u}{s} & -\frac{a_i^u}{s}e^{-\bar{\tau}_i s}\\ \frac{a_i^d}{s}e^{-\bar{\tau}_i s} & -\frac{a_i^d}{s}\end{pmatrix}\begin{pmatrix}\hat{\mathrm{q}}_{i-1}(s)\\ \hat{\mathrm{q}}_i(s) + \mathrm{p}_i(s)\end{pmatrix}. \tag{12}$$

The parameter a_i^u (respectively, a_i^d) corresponds to the inverse of the equivalent backwater area for the upstream (respectively, downstream) water level, and the parameter $\bar{\tau}_i$

[1] Distributed withdrawals have been considered elsewhere [15], [24]. The FDI scheme presented in Section III can be extended to the case of distributed withdrawals by suitable expansion of the observer bank.

[2] The integrator-delay-zero (IDZ) model in [25] also accounts for high frequencies by using a constant gain (in addition to an integrator and a delay).

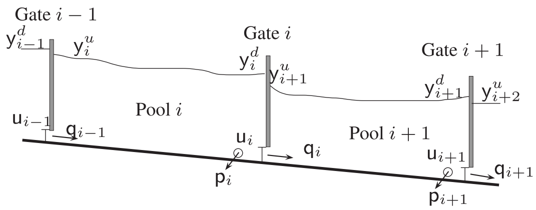

Fig. 1. Schematic view of a multipool canal system (backwater flow configuration).

(respectively, $\underline{\tau}_i$) is the upstream (respectively, downstream) propagation time delays, i.e., the minimum time for a change in the downstream (respectively, upstream) discharge to have an effect on the upstream (respectively, downstream) water level. For uniform flow, these parameters can be obtained analytically [4]

$$a_i^u = \frac{\gamma_i}{\alpha_i \beta_i \bar{\mathrm{T}}_i \left(e^{\frac{\gamma_i l_i}{\alpha_i \beta_i}} - 1\right)}$$
$$a_i^d = \frac{\gamma_i}{\alpha_i \beta_i \bar{\mathrm{T}}_i \left(1 - e^{-\frac{\gamma_i l_i}{\alpha_i \beta_i}}\right)}$$
$$\underline{\tau}_i = \frac{l_i}{\alpha_i}, \quad \bar{\tau}_i = \frac{l_i}{\beta_i}.$$

For nonuniform flow, these parameters can be computed via direct system identification [1] or model reduction by numerically approximating the flow by several (virtual) uniform flow pools (see [4, Ch. 4]). Notice that (12) accounts for the influence of both upstream and downstream discharge deviations and thus, captures the input–output behavior in backwater flow configurations (Example 1 and Fig. 1 below).

In the time-domain, we have the following ODE with delayed inputs

$$\begin{aligned} \dot{\mathrm{y}}_i^u(t) &= a_i^u \mathrm{q}_{i-1}(t) - a_i^u \left[\mathrm{q}_i(t-\bar{\tau}_i) + \mathrm{p}_i(t-\bar{\tau}_i)\right] \\ \dot{\mathrm{y}}_i^d(t) &= a_i^d \mathrm{q}_{i-1}(t-\underline{\tau}_i) - a_i^d \left[\mathrm{q}_i(t) + \mathrm{p}_i(t)\right]. \end{aligned} \tag{13}$$

Combining (11) and (13) gives the delay-differential equation

$$\begin{aligned} \dot{\mathrm{y}}_i^u(t) &= a_i^u \left[b_{i-1}^d \mathrm{y}_{i-1}^d(t) + b_i^u \mathrm{y}_i^u(t)\right] \\ &\quad - a_i^u \left[b_i^d \mathrm{y}_i^d(t-\bar{\tau}_i) + b_{i+1}^u \mathrm{y}_{i+1}^u(t-\bar{\tau}_i)\right] \\ &\quad + a_i^u \left[k_{i-1}\mathrm{u}_{i-1}(t) - k_i \mathrm{u}_i(t-\bar{\tau}_i) + \mathrm{p}_i(t-\bar{\tau}_i)\right] \\ \dot{\mathrm{y}}_i^d(t) &= a_i^d \left[b_{i-1}^d \mathrm{y}_{i-1}^d(t-\underline{\tau}_i) + b_i^u \mathrm{y}_i^u(t-\underline{\tau}_i) + \right] \\ &\quad - a_i^d \left[b_i^d \mathrm{y}_i^d(t) + b_{i+1}^u \mathrm{y}_{i+1}^u(t)\right] \\ &\quad + a_i^d \left[k_{i-1}\mathrm{u}_{i-1}(t-\underline{\tau}_i) - k_i \mathrm{u}_i(t) - \mathrm{p}_i(t)\right]. \end{aligned} \tag{14}$$

We now consider the specific case of a two-pool ($m = 2$) canal with three submerged hydraulic gates (Fig. 1 and consider $i = 1$). For sake of simplicity, we will assume that the upstream level at gate 0 and downstream level at gate 2 are constant, i.e., $\mathrm{y}_0^d = 0$ and $\mathrm{y}_3^u = 0$, and moreover, the opening of gate 2 is fixed, i.e., $\mathrm{u}_2 = 0$. The full model for the two-pool system can be written in state-space form as follows:

$$\begin{aligned} \dot{\mathrm{x}}(t) &= \sum_{i=0}^{4} A_i \mathrm{x}(t-\tau_i) + \sum_{i=0}^{4} B_i \mathrm{u}(t-\tau_i) \\ \mathrm{y}(t) &= C\mathrm{x}(t) \end{aligned} \tag{15}$$

where $\mathrm{x} := \left(\mathrm{y}_1^u, \mathrm{y}_2^u, \mathrm{y}_1^d, \mathrm{y}_2^d\right)^{\mathsf{T}} \in \mathbb{R}^4$ is the state, $\mathrm{u} := \left(\mathrm{u}_0, \mathrm{u}_1, \mathrm{p}_1, \mathrm{p}_2\right)^{\mathsf{T}} \in \mathbb{R}^4$ denotes the known input, $\mathrm{y} := \left(\mathrm{y}_1^u, \mathrm{y}_2^u, \mathrm{y}_1^d, \mathrm{y}_2^d\right)^{\mathsf{T}} \in \mathbb{R}^4$ is the measured output; $\tau_0 = 0$, $\tau_1 = \bar{\tau}_1$, $\tau_2 = \underline{\tau}_1$, $\tau_3 = \bar{\tau}_2$, $\tau_4 = \underline{\tau}_2$. The matrices C, A_i, B_i are known matrices in $\mathbb{R}^{4\times 4}$ which are, respectively, given by $C = \mathrm{diag}\left(1, 1, 1, 1\right)$, and

$$A_0 = \begin{pmatrix} a_1^u b_1^u & 0 & 0 & 0 \\ 0 & a_2^u b_2^u & a_2^u b_1^d & 0 \\ 0 & -a_1^d b_2^u & -a_1^d b_1^d & 0 \\ 0 & 0 & 0 & -a_2^d b_2^d \end{pmatrix}$$

$$B_0 = \begin{pmatrix} a_1^u k_0 & 0 & 0 & 0 \\ 0 & a_2^u k_1 & 0 & 0 \\ 0 & -a_1^d k_1 & -a_1^d & 0 \\ 0 & 0 & 0 & -a_2^d \end{pmatrix}$$

$$A_1 = \begin{pmatrix} 0 & -a_1^u b_2^u & -a_1^u b_1^d & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$B_1 = \begin{pmatrix} 0 & -a_1^u k_1 & -a_1^u & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$A_2 = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ a_1^d b_1^u & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$B_2 = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ a_1^d k_0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$A_3 = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -a_2^u b_2^d \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$B_3 = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -a_2^u \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$A_4 = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & a_2^d b_2^u & a_2^d b_1^d & 0 \end{pmatrix}$$

$$B_4 = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & a_2^d k_1 & 0 & 0 \end{pmatrix}.$$

Consider the case of unmeasured water withdrawals [denoted $\delta \mathrm{p}_i(t)$] occurring through the offtakes, located at the downstream ends (see Fig. 1). Equation (15) now becomes

$$\begin{aligned} \dot{\mathrm{x}}(t) &= \sum_{i=0}^{4} A_i \mathrm{x}(t-\tau_i) + \sum_{i=0}^{4} B_i \mathrm{u}(t-\tau_i) + \sum_{i=1}^{2} E_i f_i(t) \\ \mathrm{y}(t) &= C\mathrm{x}(t) \end{aligned} \tag{16}$$

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where

$$f_i(t) = \left(\delta \mathrm{p}_i(t)\ \delta\tilde{\mathrm{p}}_i(t)\right)^{\mathsf{T}}, \qquad i = 1, 2$$

$$E_1 = \begin{pmatrix} 0 & -a_1^u & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ -a_1^d & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

$$E_2 = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -a_2^u & 0 \\ 0 & 0 & 0 & 0 & 0 \\ -a_2^d & 0 & 0 & 0 & 0 \end{pmatrix}. \tag{17}$$

with $\delta\tilde{\mathrm{p}}_i(t) := \left(\delta \mathrm{p}_i(t-\tau_1) \cdots \delta \mathrm{p}_i(t-\tau_4)\right)$.

We will consider the following numerical example of a two-pool system throughout the paper.

Example 1: Two-pool system in backwater configuration Consider (16) with following parameters: upstream (respectively, downstream) propagation delays $\bar{\tau}_1 = 846.5$ s, $\bar{\tau}_2 = 750.5$ s (respectively, $\underline{\tau}_1 = 707.5$ s, $\underline{\tau}_2 = 647.5$ s), equivalent inverse backwater areas for upstream (respectively, downstream) water levels $a_1^u = 3.975 \times 10^{-5}$ m^{-2}, $a_2^u = 3.675 \times 10^{-5}$ m^{-2} (respectively, $a_1^d = 3.21 \times 10^{-5}$ m^{-2}, $a_2^d = 3.115 \times 10^{-5}$ m^{-2}) . Let the coefficients of linearized gate equations $b_1^d = 20.0, b_2^d = 29.0, b_1^u = -21.36, b_2^u = -25.36, k_0 = 18.1$, and $k_2 = 12.1$. Assume that $\mathrm{u}(t) = 0$ for $t \in [-\underline{\tau}_1, \infty)$ and $\mathrm{x}(t) = 0$ for $t \in [-\underline{\tau}_1, 0]$. Water at the rate 0.1 m^3/s is withdrawn from offtake of pool 1 (respectively, pool 2) during the interval $2.5 - 5.0$ h (respectively, $15 - 17.5$ h).

Fig. 2 shows the upstream and downstream water level deviations under the effect of unmeasured withdrawals during a 24 h simulation. Notice that, in contrast to the model in [10], (16) captures the time delays in both upstream and downstream propagation of level deviations due to pool withdrawals.

III. UIO-Based FDI

In this section, we present the design of UIO for linear time delay systems when unknown inputs are present in both state and measurement equations. A bank of UIO observers so designed are then used for detection and isolation under coupled disturbance/fault signals.

A. UIO Design

Consider the following linear, time-invariant, delay differential system (DDS) with unknown inputs

$$\begin{aligned} \dot{\mathrm{x}}(t) &= \sum_{i=0}^{r} A_i \mathrm{x}(t-\tau_i(t)) + \sum_{i=1}^{r} B_i \mathrm{u}(t-\tau_i(t)) + Ef(t) \\ \mathrm{x}(\theta) &= \rho_1(\theta), \mathrm{u}(\theta) = \rho_2(\theta), \qquad \theta \in [-\tau_{\max}, 0] \\ \mathrm{y}(t) &= C\mathrm{x}(t) + Hf(t) \end{aligned} \tag{18}$$

where $\mathrm{x}(t) \in \mathbb{R}^n$ is the state vector, $\mathrm{u}(t) \in \mathbb{R}^m$ is the known input vector, $f \in \mathbb{R}^q$ the unknown input vector, $\mathrm{y} \in \mathbb{R}^p$ the measurement output vector, and $\rho_1 \in \mathbb{R}^n$ and $\rho_2 \in \mathbb{R}^m$ are initial vector functions for the state and input. The matrices A_i, B_i, C, and E are known real matrices of appropriate dimensions. The matrix E (respectively, H) is called the disturbance distribution matrix for state (respectively, observation) equation, and $Hf(t)$ [respectively, $Ef(t)$] determines the unknown sensor disturbance (respectively, unknown input uncertainty). The delays $\tau_i(t)$ are bounded but possibly time varying, and satisfy[3]

$$\begin{aligned} \tau_i(t) &\leqslant h_i \quad \dot{\tau}_i(t) \leqslant d_i < 1, \qquad i = 1, \ldots, r \\ \tau_{\max} &:= \max\{h_1, \ldots, h_r\} \end{aligned} \tag{19}$$

where h_i and d_i are known constants.

Consider the following full-order observer for (18)

$$\begin{aligned} \dot{\mathrm{z}}(t) &= \sum_{i=0}^{r} F_i \mathrm{z}(t-\tau_i) + \sum_{i=0}^{r} TB_i u(t-\tau_i) + \sum_{i=0}^{r} G_i \mathrm{y}(t-\tau_i) \\ \mathrm{z}(\theta) &= \rho_3(\theta), \quad \theta \in [-\tau_{\max}, 0] \\ \hat{\mathrm{x}}(t) &= \mathrm{z}(t) + N\mathrm{y}(t) \end{aligned} \tag{20}$$

where $\mathrm{z}(t) \in \mathbb{R}^n$ is the observer state vector, $\rho_3 \in \mathbb{R}^n$ the initial vector function, and $\hat{\mathrm{x}}(t)$ the estimate of $\mathrm{x}(t)$. The matrices F_i, G_i, T, and N are constant matrices of appropriate dimensions which must be determined such that $\hat{\mathrm{x}}(t)$ asymptotically converges to $\mathrm{x}(t)$, regardless of the presence of unknown inputs $f(t)$. Such an observer, if it exists, achieves perfect decoupling from the unknown inputs. We define the error between $\mathrm{x}(t)$ and its estimate $\hat{\mathrm{x}}(t)$ as

$$\mathrm{e}(t) = \hat{\mathrm{x}}(t) - \mathrm{x}(t) = \mathrm{z}(t) - T\mathrm{x}(t) + NHf(t)$$

where $T = \mathrm{I}_n - NC$. The error dynamics are given by

$$\begin{aligned} \dot{\mathrm{e}}(t) = &\sum_{i=0}^{r} F_i \mathrm{e}(t-\tau_i) \\ &+ (F_i - TA_i + (G_i - F_i N)C)\,\mathrm{x}(t-\tau_i) \\ &- (TE + F_0 NH - G_0 H)\, f(t) \\ &- \sum_{i=1}^{r} (F_i N - G_i)\, Hf(t-\tau_i) + NH\dot{f}(t). \end{aligned} \tag{21}$$

[3]Time-varying delays in automated canal systems can result via a communication network which transmits the sensor-control data packets.

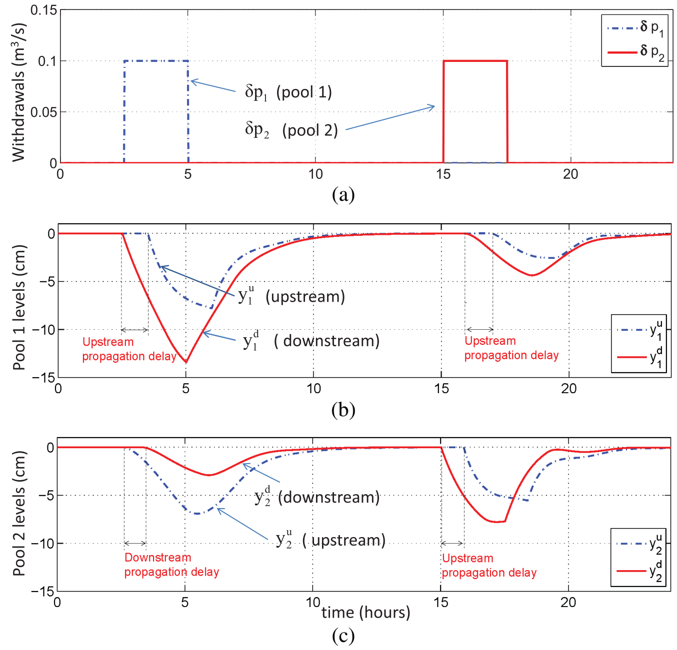

Fig. 2. Example two-pool system. (a) Withdrawals. (b) Pool 1. (c) Pool 2 level deviations.

Then it is straightforward to obtain the following result.

Theorem 2: The full order observer (20) will asymptotically estimate $\mathrm{x}(t)$ if the following conditions hold.

1) $\dot{\mathrm{e}}(t) = \sum_{i=0}^{r} F_i \mathrm{e}(t - \tau_i)$ is asymptotically stable.
2) $\mathrm{I}_n = T + NC$.
3) $\bar{G}_i = G_i - F_i N, \quad i = 0, \ldots, r$.
4) $F_i = TA_i - \bar{G}_i C, \quad i = 0, \ldots, r$.
5) $\bar{G}_0 H = TE$.
6) $\bar{G}_i H = 0, \quad i = 1, \ldots, r$.
7) $NH = 0$.

Thus, the observer design problem is reduced to finding the matrices T, N, and $F_i, \bar{G}_i$, $i = 0, \ldots, r$ such that the conditions in Theorem 2 are satisfied. For $r = 4$, i.e., the case for two-pool system, (2)–(7) in Theorem 2 can be written as follows:

$$S\Theta = \Psi \tag{22}$$

where

$$\begin{aligned} S &= \begin{pmatrix} T & N & F_0 & \bar{G}_0 & \cdots & F_4 & \bar{G}_4 \end{pmatrix} \in \mathbb{R}^{n\times(6n+6p)} \\ \Theta &= \begin{pmatrix} \Theta_1 & \Theta_2 & \Theta_3 \end{pmatrix} \in \mathbb{R}^{(6n+6p)\times(6n+6q)} \\ \Psi &= \begin{pmatrix} \mathrm{I}_n & 0 \end{pmatrix} \in \mathbb{R}^{n\times(6n+6q)} \end{aligned}$$

with Θ_1, Θ_2, and Θ_3 given by

$$\Theta_1 = \begin{pmatrix} \mathrm{I}_n & E \\ C & 0 \\ 0 & 0 \\ 0 & -H \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}$$

$$\Theta_2 = \begin{pmatrix} A_0 & A_1 & A_2 & A_3 & A_4 \\ 0 & 0 & 0 & 0 & 0 \\ -\mathrm{I}_n & 0 & 0 & 0 & 0 \\ -C & 0 & 0 & 0 & 0 \\ 0 & -\mathrm{I}_n & 0 & 0 & 0 \\ 0 & -C & 0 & 0 & 0 \\ 0 & 0 & -\mathrm{I}_n & 0 & 0 \\ 0 & 0 & -C & 0 & 0 \\ 0 & 0 & 0 & -\mathrm{I}_n & 0 \\ 0 & 0 & 0 & -C & 0 \\ 0 & 0 & 0 & 0 & -\mathrm{I}_n \\ 0 & 0 & 0 & 0 & -C \end{pmatrix}$$

$$\Theta_3 = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ H & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & H & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & H & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & H & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & H \end{pmatrix}.$$

Following the general solution of a set of linear matrix equations (see [13]), there exists a solution to (22) if and only if

$$\mathrm{rank}\begin{pmatrix} \Theta \\ \Psi \end{pmatrix} = \mathrm{rank}\begin{pmatrix} \Theta \end{pmatrix}$$

or equivalently

$$\mathrm{rank}\begin{pmatrix} \mathrm{CE} \\ H \end{pmatrix} = \mathrm{rank}\begin{pmatrix} E \\ H \end{pmatrix}. \tag{23}$$

Under the above rank condition, a general solution of (22) is

$$S = \Psi\Theta^{+} - K(I - \Theta\Theta^{+}) \tag{24}$$

where K is an arbitrary matrix of appropriate dimension, and Θ^{+} is the generalized inverse matrix of Θ given by $\Theta^{+} = (\Theta^{\mathsf{T}}\Theta)^{-1}\Theta$ since Θ is of full column rank. The choice of K is important in determining the asymptotic stability of the observer. This can be seen by inserting (24) into condition (4) of Theorem 2. The matrices F_i can now be expressed as

$$F_i = \chi_i - K\beta_i, \quad i = 0, 1, \ldots, 4 \tag{25}$$

where

$$\begin{aligned} \chi_0 &= \Psi\Theta^{+}\begin{pmatrix} A_0 & 0 & 0 & -C & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}^{\mathsf{T}} \\ \chi_1 &= \Psi\Theta^{+}\begin{pmatrix} A_0 & 0 & 0 & 0 & 0 & -C & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}^{\mathsf{T}} \\ \chi_2 &= \Psi\Theta^{+}\begin{pmatrix} A_0 & 0 & 0 & 0 & 0 & 0 & 0 & -C & 0 & 0 & 0 & 0 \end{pmatrix}^{\mathsf{T}} \\ \chi_3 &= \Psi\Theta^{+}\begin{pmatrix} A_0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -C & 0 & 0 \end{pmatrix}^{\mathsf{T}} \\ \chi_4 &= \Psi\Theta^{+}\begin{pmatrix} A_0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -C \end{pmatrix}^{\mathsf{T}} \\ \beta_0 &= \tilde{\Theta}\begin{pmatrix} A_0 & 0 & 0 & -C & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}^{\mathsf{T}} \\ \beta_1 &= \tilde{\Theta}\begin{pmatrix} A_0 & 0 & 0 & 0 & 0 & -C & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}^{\mathsf{T}} \\ \beta_2 &= \tilde{\Theta}\begin{pmatrix} A_0 & 0 & 0 & 0 & 0 & 0 & 0 & -C & 0 & 0 & 0 & 0 \end{pmatrix}^{\mathsf{T}} \\ \beta_3 &= \tilde{\Theta}\begin{pmatrix} A_0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -C & 0 & 0 \end{pmatrix}^{\mathsf{T}} \\ \beta_4 &= \tilde{\Theta}\begin{pmatrix} A_0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -C \end{pmatrix}^{\mathsf{T}} \end{aligned}$$

with $\tilde{\Theta} := (I - \Theta\Theta^{+})$. Under (23), and from above results, the error dynamics (21) for $r = 4$ can be written as

$$\dot{\mathrm{e}}(t) = \sum_{i=0}^{4}(\chi_i - K\beta_i)\mathrm{e}(t - \tau_i(t)). \tag{26}$$

Thus, the problem of observer (20) design reduces to the determination of the matrix parameter K such that the stability condition (1) of Theorem 2 holds. We now give delay-dependent conditions for the stability of the observer under the delay bounds (19). By extension, similar conditions can be determined for any r.

Proposition 3: Suppose that condition (23) is satisfied, and let $r = 4$. Then there exists an asymptotically stable UIO (20), if for some scalars $\epsilon_0, \ldots, \epsilon_9$ and $\bar{\epsilon}_1, \ldots, \bar{\epsilon}_4$, there exist matrices $S_i > 0$, $Z_i > 0$, $Q_i > 0$, $R_i > 0$, U_i, W_i, $i = 1, \ldots, 4$, and matrices H_i, $i = 0, \ldots, 9$, U and $P > 0$

such that the following linear matrix inequalities are satisfied:

$$\begin{pmatrix} Q_i & U_i \\ U_i^{\top} & R_i \end{pmatrix} \geqslant 0, \qquad i = 1, \dots, 4 \tag{27}$$

$$\begin{pmatrix} \Phi & h_1\bar{H}_1 & h_2\bar{H}_2 & h_3\bar{H}_3 & h_4\bar{H}_4 \\ * & -h_1\bar{Z}_1 & 0 & 0 & 0 \\ * & * & -h_2\bar{Z}_2 & 0 & 0 \\ * & * & * & -h_3\bar{Z}_3 & 0 \\ * & * & * & * & -h_4\bar{Z}_4 \end{pmatrix} < 0 \tag{28}$$

where

$$\bar{Z}_i := \begin{pmatrix} S_i & W_i \\ W_i^{\top} & Z_i \end{pmatrix} \quad \bar{H}_i := \begin{pmatrix} -\bar{\epsilon}_i(P\chi_0 - U\beta_0)^{\top} & H_0 \\ -\bar{\epsilon}_i(P\chi_1 - U\beta_1)^{\top} & H_1 \\ -\bar{\epsilon}_i(P\chi_2 - U\beta_2)^{\top} & H_2 \\ -\bar{\epsilon}_i(P\chi_3 - U\beta_3)^{\top} & H_3 \\ -\bar{\epsilon}_i(P\chi_4 - U\beta_4)^{\top} & H_4 \\ \bar{\epsilon}_i P & H_5 \\ 0 & H_6 \\ 0 & H_7 \\ 0 & H_8 \\ 0 & H_9 \end{pmatrix} \tag{29}$$

for $i = 1, \dots, 4$, and $\Phi = (\phi_{jk})$ is a symmetric matrix of the form (44) with block elements ϕ_{jk}; see Appendix V. The parameter matrix K is given by $K = P^{-1}U$.

The proof is presented in Appendix V. We now present our FDI scheme for the delay-differential system of the form (18), which uses the LMI method of Proposition 3.

B. Residual Generation

Consider jth DDS, $j = 1, \dots, s$, with s candidate fault signals

$$\begin{aligned} \dot{\mathrm{x}}_j(t) &= \sum_{i=0}^{r} A_i \mathrm{x}_j(t - \tau_i) + \sum_{i=1}^{r} B_i \mathrm{u}_j(t - \tau_i) + \sum_{i=1}^{s} E_i f_i(t) \\ \mathrm{y}_j(t) &= C\mathrm{x}_j(t) + \sum_{i=1}^{s} H_i f_i(t). \end{aligned} \tag{30}$$

The FDI scheme we consider here is required to detect the occurrence as well as isolate an unknown signal $f_j(t)$ from other unknown signals $f_k(t)$ $k \neq j$. Each unknown signal models a coupled disturbance/fault in the state and measurement equations. Following [12], we consider the problem of residual generation according to following definition.

Definition 1 (Residual Generation Problem): The problem consists of finding residuals $\mathrm{r}_j(t)$ defined as follows:

$$\mathrm{r}_j(t) := \mathrm{y}_j(t) - C\hat{\mathrm{x}}_j(t), \qquad j = 1, \dots, s \tag{31}$$

where $\hat{\mathrm{x}}_j(t)$ is the output of the jth UIO of the form (20), and $\mathrm{y}_j(t)$ is the output of (30), with the following properties.

1) $\mathrm{r}_j(t)$ is insensitive (i.e., robust) to $f_j(t)$.
2) $\mathrm{r}_j(t)$ converges to zero asymptotically if $f_k(t) = 0, k \neq j$ for every t.
3) $\|\mathrm{r}_j(t)\| \neq 0$ when $f_k(t) \neq 0$ for $k \neq j$.[4]

[4]In [12], this condition is generalized to $\exists p \geqslant 0$ such that $\frac{d}{df_k}\left(\frac{d^p \mathrm{r}_j(t)}{dt^p}\right) \neq 0$ for $k \neq j$.

If the residuals $\mathrm{r}_i(t)$ $i = 1, \dots, s$ satisfy the properties of Definition 1, fault diagnosis can be successfully achieved (i.e., perfect decoupling) based on the following decision rule:

$$f_j(t) \neq 0 \text{ if } \|\mathrm{r}_j(t)\| \approx 0 \text{ and } \|\mathrm{r}_k(t)\| \neq 0, k \neq j. \tag{32}$$

We now discuss the FDI scheme for nonsimultaneous withdrawals for the two-pool system.

Example 4 (FDI Scheme for Unknown Withdrawals): System (30) models a two-pool system with $r = 4$, $s = 2$. Assume E_1 and E_2 are of the form (17), $H_1 = H_2 = 0$, all other parameters as in Example 1, and zero known input signal $\mathrm{u}(t) = 0$ (the system evolves in open-loop). Let the unknown withdrawal from pool 1 (respectively, pool 2) during the interval 2.5−5.0 h (respectively, 15−17.5 h) be the fault signal $f_1(t)$ [respectively, $f_2(t)$]. Assume the bounds of the time delays $\tau_i(t)$ to be 1.1 times their nominal values, i.e., $h_1 = 1.1 \times \bar{\tau}_1$, and so on; and the time derivatives of the delays all less than 0.1, i.e., $d_i < 0.1$. Two observers are designed as follows.

Observer 1 (respectively, observer 2) is designed to be insensitive to $f_1(t)$ [respectively, $f_2(t)$]. Residual $\mathrm{r}_j(t)$ $j = 1, 2$ of the jth observer is defined by (31), and $\hat{\mathrm{x}}_j(t)$ is the output of jth UIO designed for the following model:

$$\begin{aligned} \dot{\mathrm{x}}_j(t) &= \sum_{i=0}^{4} A_i \mathrm{x}_j(t - \tau_i) + \sum_{i=0}^{4} B_i \mathrm{u}_j(t - \tau_i) \\ &\quad + E_j f_j(t) + E_{-j} f_{-j}(t) \\ \mathrm{y}_j(t) &= C\mathrm{x}_j(t) \end{aligned} \tag{33}$$

where $-j := (3 - j)$. In (33) $f_2(t) = 0$ (respectively, $f_1(t) = 0$) for observer 1 (respectively, observer 2). The LMI conditions in Proposition 3 are feasible for $\epsilon_0 = 10$, $\epsilon_1 = \dots = \epsilon_9 = -1$, and $\bar{\epsilon}_1 = \dots = \bar{\epsilon}_4 = -1$, and the parameter matrices F_{ij}, G_{ij}, T_j and N_j $(i = 0, \dots, 4)$ are obtained for the observers

$$\begin{aligned} \dot{\mathrm{z}}_j(t) &= \sum_{i=0}^{4} F_{ij} \mathrm{z}_j(t - \tau_i) + \sum_{i=0}^{4} T_j B_i u_j(t - \tau_i) + \sum_{i=0}^{4} G_{ij} \mathrm{y}_j(t - \tau_i) \\ \hat{\mathrm{x}}_j(t) &= \mathrm{z}_j(t) + N_j \mathrm{y}_j(t). \end{aligned}$$

From the computed observer matrices T_1 and T_2, we obtain

$$T_1 E_1 = 10^{-15} \times \begin{pmatrix} 0.040 & 0.041 & 0 & 0 \\ -0.286 & -0.054 & 0 & 0 \\ 0.241 & 0.010 & 0 & 0 \\ -0.388 & -0.330 & 0 & 0 \end{pmatrix} \approx 0$$

$$T_1 E_2 = \begin{pmatrix} -0.000 & 0 & 0 & -0.000 & 0 \\ 0.288 & 0 & 0 & 0.149 & 0 \\ -0.383 & 0 & 0 & -0.021 & 0 \\ 0.044 & 0 & 0 & 0.289 & 0 \end{pmatrix} \neq 0$$

$$T_2 E_1 = \begin{pmatrix} 0.523 & -0.106 & 0 & 0 & 0 \\ -0.077 & 0.074 & 0 & 0 & 0 \\ -0.026 & 0.479 & 0 & 0 & 0 \\ 0.000 & 0.000 & 0 & 0 & 0 \end{pmatrix} \neq 0$$

$$T_2 E_2 = 10^{-14} \times \begin{pmatrix} -0.014 & 0 & 0 & -0.007 & 0 \\ 0.008 & 0 & 0 & -0.006 & 0 \\ 0.002 & 0 & 0 & -0.001 & 0 \\ 0.150 & 0 & 0 & -0.227 & 0 \end{pmatrix} \approx 0.$$

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We can check that the residuals $r_j(t)$ $j = 1, 2$ in Example 4 satisfy the properties of Definition 1:

1) $r_1(t)$ (respectively, $r_2(t)$) is insensitive to $f_1(t)$ ($f_2(t)$) (follows from UIO property of observers 1 and 2);
2) the residual dynamics defined by
$$\dot{r}_j(t) = C\left(\sum_{i=0}^{4} F_{ij} e_j(t - \tau_i)\right)$$
converges to zero asymptotically when $f_{-j}(t) = 0$ for every t because the conditions of Theorem 2 are satisfied (e.g., $T_1 E_1 = T_2 E_2 = 0$);
3) $\|r_j(t)\| \neq 0$ when $f_{-j}(t) \neq 0$ since $T_j E_{-j} \neq 0$, $j = 1, 2$.

Hence, the FDI scheme for the above example can be achieved using the decision rule 32. From Fig. 3, we can observe that the generated residuals successfully achieve FDI.

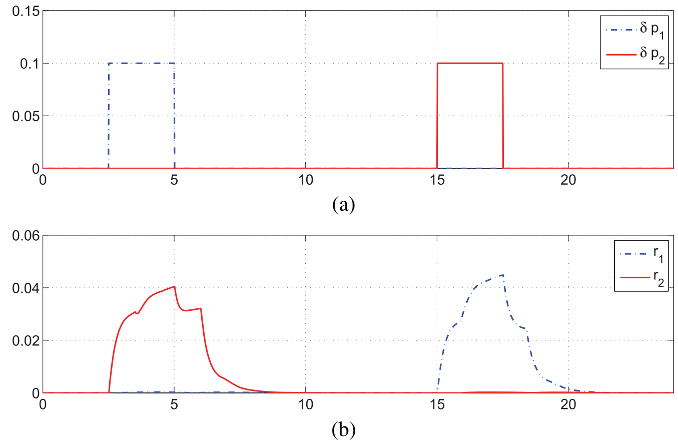

Fig. 3. (a) Fault signals δp_1 and δp_2 and (b) norms of residuals r_1 and r_2 corresponding to observer 1 and 2, respectively.

IV. ADI

In this section, we study the performance of the FDI scheme designed in Section III on a generalized fault/attack model. This model allows the modeling of many adversarial scenarios in which, differently from faults, the failure signals in the state and measurement equations are uncoupled. For the sake of simplicity, we will only consider the two-pool system, noting that similar analysis can be performed for multipool systems.

A. Generalized Fault/Attack Model for Two Pool System

Consider the DDS when fault/disturbances signals in the input and sensor measurements appear in uncoupled forms

$$\Sigma_a = \begin{cases} \dot{x}(t) = & \sum_{i=0}^{4} A_i x(t - \tau_i) + \sum_{i=0}^{4} B_i u(t - \tau_i) \\ & + \sum_{i=0}^{s} E_i f_i(t) \\ y(t) = & Cx(t) + \sum_{i=0}^{s} H_i g_i(t) \end{cases} \tag{34}$$

where, $f_i(t)$ and $g_i(t)$ with $i = 1, \ldots, s$ are fault/disturbance signals affecting the state and measurement equations. Notice that this is in contrast to (30) where these signals are linearly coupled. We now show that (34) can represent traditional faults, such as nonsimultaneous discharge withdrawals (leaks) or sensor-actuator faults, and many adversarial scenarios when these disturbances can be manifested simultaneously.

1) Leaks and Sensor-Actuator Faults: Unmeasured withdrawals or leaks [denoted $\delta p_i(t)$] may be caused by random faults or deliberate tampering of offtakes [22]. For (34), such discharge withdrawals can be modeled by considering $s = 2$, $H_1 = 0$, $H_2 = 0$, and E_1 and E_2 given by (17) (see Example 1). Similarly, we can model the actuator fault [denoted $\delta u_i(t)$] caused due to blockage of hydraulic structures or intentional manipulation of control actions. Consider, for example, $H_1 = 0$, and $H_2 = 0$, and

$$f_i(t) = \left(\delta u_i(t)\ \delta\tilde{u}_i(t)\right)^{\mathsf{T}}$$
$$E_1 = \begin{pmatrix} a_1^u k_0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & a_1^d k_0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$
$$E_2 = \begin{pmatrix} 0 & -a_1^u k_1 & 0 & 0 & 0 \\ a_2^u k_1 & 0 & 0 & 0 & 0 \\ -a_1^d k_1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & a_2^d k_1 \end{pmatrix}$$

with $\delta\tilde{u}_i(t) := \left(\delta u_i(t - \tau_1) \cdots \delta u_i(t - \tau_4)\right)$. The sensor signals $y_i^u(t)$ and $y_i^d(t)$ may be subjected to random faults [21] (e.g., effect of temperature variations in pressure sensors, malfunction of electronic circuitry in ultrasonic sensors), or b) adversarial biases which distort the true sensor signals (e.g., false-data injection attack [24]). Sensor failures (denoted $\delta y_i(t)$) in (34) can be modeled by considering $s = 2$, $E_1 = 0$, and $E_2 = 0$

$$g_i(t) = \left(\delta y_i^u(t)\ \delta y_i^d(t)\right)^{\mathsf{T}}, \quad i = 1, 2$$
$$H_1 = \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \end{pmatrix} \quad H_2 = \begin{pmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{pmatrix}. \tag{35}$$

In many situations, faults/disturbance signals can appear in both measurement and state evolution equations in a linearly coupled manner, i.e., $f_i(t) = g_i(t)$ and (34) takes the same form as (18). For example, when a level sensor measurement is subjected to an additive bias and is injected in the system via output feedback control, the same bias will enter in the state equation as well.

Finally, note that the scheme proposed in Section III can be extended to achieve detection and isolation of faults in all the above mentioned, scenarios under the assumption of nonsimultaneous faults (i.e., if $f_i(t) \neq 0$, then $f_j(t) = 0$ where $j \neq i$).

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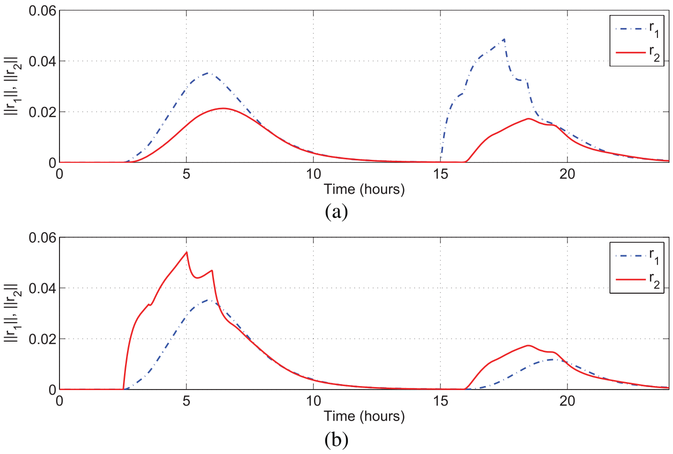

Fig. 4. Attack on individual pools. (a) Residuals under attack on y_1^u and y_1^d. (b) Residuals under attack on y_2^u and y_2^d.

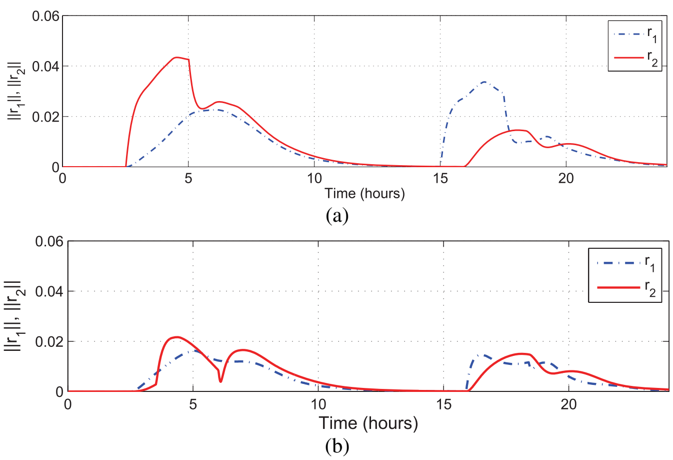

Fig. 5. Attack on upstream and downstream levels. (a) Residuals under attack on y_1^u and y_2^u. (b) Residuals under attack on y_1^d and y_2^d.

2) Simultaneous and Uncoupled Attacks: In many adversarial scenarios, the faults or disturbances on inputs and measurements can enter in an uncoupled manner [i.e., $f_i(t) \neq \mathrm{g}_i(t)$ in (34)]. Moreover, they can manifest simultaneously. Consider an adversarial scenario for system (34) when a deception attack simultaneously causes distortion of true sensor signals and unknown water withdrawal from the offtake. This scenario can be modeled with $f_i(t)$, E_1 and E_2 (respectively, $\mathrm{g}_i(t)$, H_1 and H_2) given by (17) [respectively, (35)]. This attack was the main focus of [10], where it was shown that a deception attack on sensor signals prevented correct isolation of unknown withdrawals.

In general, without any prior knowledge of attack signals, the FDI scheme of Section III cannot be extended to such adversarial scenarios. In the following example, we evaluate the performance of this scheme on different adversarial scenarios.

Example 5: Consider the FDI scheme designed in Example 4, which generated correct residuals to detect and isolate nonsimultaneous withdrawals for two-pool system. To evaluate the performance of this scheme when the true sensor measurements are spoofed with an additive deception attack, we consider four cases: 1) for each pool i, y_i^u and y_i^d are spoofed simultaneously (Fig. 4); 2) both y_1^u and y_2^u are spoofed simultaneously; similarly for y_1^d and y_2^d (Fig. 5); 3) middle gate measurements y_1^d, y_2^u are spoofed (Fig. 6); and 4) all y_1^u, y_1^d, and y_2^u are spoofed simultaneously; similarly for y_1^d, y_2^u, and y_2^d (Fig. 7). In all the four cases, it is assumed that the attacker injects an additive attack such that the targeted level sensor measurement signal does not deviate from zero. For example, for case 1), $\mathrm{g}_i(t) := (-\mathrm{y}_i^u(t) \ \ -\mathrm{y}_i^d(t))^{\mathsf{T}}$, where $\mathrm{y}_i^u(t)$ and $\mathrm{y}_i^d(t)$ are true measurement signals, and H_i is given by (35); similarly for other cases.

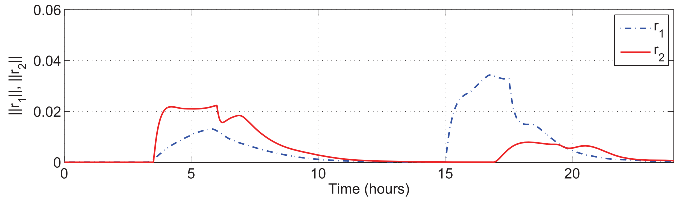

Fig. 6. Attack on the middle gate: residuals under attack on y_1^d, y_2^u.

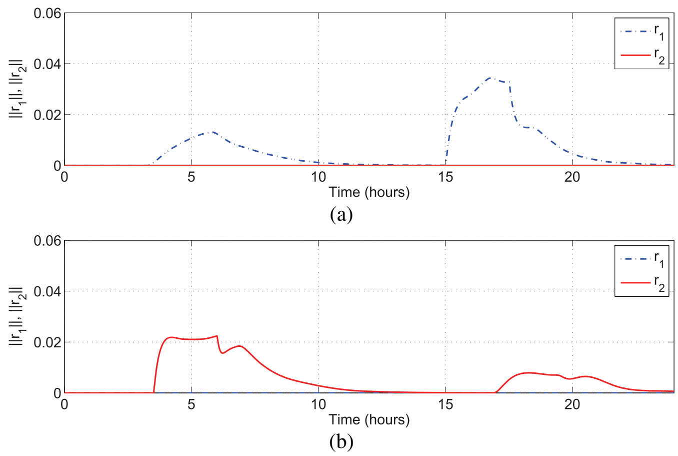

Fig. 7. Stealthy attack. (a) Residuals under attack on y_1^u, y_1^d, and y_2^u. (b) Residuals under attack on y_1^d, y_2^u, and y_2^d.

B. Implications for Water Security

Based on the performance of our FDI scheme on adversarial scenarios from the generalized attack model (34), and in particular from the deception attack scenarios of Example 5, we can make several interesting observations. First, the rule (32) can no longer be used to diagnose fault/attack scenarios when the observer residuals do not satisfy the conditions for perfect decoupling in Definition 1. However, in certain adversarial scenarios, e.g., the case when y_1^u and y_2^u are spoofed in Fig. 5(a), an acceptable diagnostic performance (i.e., approximate decoupling) can be achieved using the following F/ADI rule

$$f_j(t) \neq 0 \text{ if } \left\|\mathrm{r}_j(t)\right\| < \vartheta_{f_j} \text{ and } \|\mathrm{r}_k(t)\| \geqslant \vartheta_{f_k}, \qquad k \neq j \quad (36)$$

where the parameters ϑ_{f_i} $i = 1, \ldots, s$ are the isolation thresholds of the F/ADI scheme. These parameters can be constant or time varying depending on the nature fault/attack scenarios, and determine the expected false-alarm and missed-detection rates. For a discussion on the choice of isolation thresholds in fault scenarios, we refer the reader to [26] (and the reference therein). The choice of isolation thresholds becomes particularly important in security scenarios. An attacker who knows these parameters can adaptively manipulate sensor-control signals to evade detection [27].[5] However, from a practical viewpoint, these parameters can be chosen by simulation-based testing under the fault/attack scenarios that are likely to be encountered.

The F/ADI rule (36) may not successfully isolate unknown withdrawals in a pool (say i) when both y_i^u and y_i^d are compromised. For example, in Fig. 4(a), observer 1 which was designed to be insensitive to f_1 is no longer able to maintain r_1 to zero (whereas, r_2 generated by observer 2 is still sensitive to f_1). However, notice that in this case f_2 can be still be correctly isolated using (36). From this observation, it can be concluded that when both upstream and downstream measurements of a canal pool are compromised, it is difficult to isolate the local faults in the pool; however, faults in other pools can still be isolated.

Another observation is that the location of compromised sensor measurements relative to the location of the fault is an important factor for achieving successful diagnosis. We recall that, under our setting, the offtakes are located near the downstream ends (see Fig. 1). From Fig. 4(b) it can be seen that, in contrast to Fig. 4(a), the attack on downstream measurements is more detrimental to the performance of residuals in detecting unknown withdrawals from offtakes. Since our diagnosis scheme is based on the physics-based ID model (see (14) in Section II), the effect of water withdrawals is captured by both upstream and downstream level sensors; however, the effect is more pronounced at the downstream level sensors. This insight can also be applied when both measurements of a single gate are compromised. See Fig. 6 when attack on y_1^d and y_2^u of the middle gate makes the diagnosis of fault f_1 located near the gate difficult, while f_2 can still be diagnosed successfully based on (36).

The last and perhaps most interesting observation is that when sensor measurements of multiple pools are accessible to a strategic attacker, the deception attack can be perfectly stealthy, i.e., the attack can result in an incorrect diagnosis or may not be even detected! Consider Fig. 7(a) [respectively, Fig. 7(b)] when y_1^u, y_1^d, and y_2^u (respectively, y_1^d, y_2^u, and y_2^d) are compromised. Residual r_1 (respectively, r_2), which was only sensitive to fault f_2 (respectively, f_1) in the case of no attack, now reacts to both faults, whereas r_2 (respectively, r_1) is not sensitive to either fault. Following (36), this leads to incorrect diagnosis, i.e., f_1 is detected when f_2 is presented and vice versa. Moreover, from a practical viewpoint, the norms of residuals in the case of such attacks may not be high enough to enable the F/ADI rule (36) to distinguish these faults from random disturbances.

By comparing this stealthy attack with the stealthy attack reported in [10], the following remarks can be made: 1) from an attacker's point-of-view, more sensor measurements (three sensors as opposed to a single sensor in [10]) need to be compromised to achieve perfect stealthiness when the F/ADI scheme proposed herewith is used; 2) the attacker requires strategic knowledge (and perhaps more resources) to carry out such an attack; for e.g., only a particular choice of compromised measurements results in a stealthy attack; and 3) in contrast to [10] where the f_2 under the compromise of y_2^d went completely undetected since neither residuals reacted to the fault, here the residual r_2 shows a delayed response [see Fig. 7(b)]. Thus detection is not completely evaded in this case, although the diagnosis is incorrect. The observed delay is the delay in propagation of disturbance due to offtake withdrawal in the second pool to reach the upstream of first pool.

V. CONCLUSION

In this paper, we developed a model-based scheme for detection and isolation of a wide class of faults and attacks in automated canal systems. The scheme was based on a bank of UIO designed for a linear delay-differential system obtained as an analytically approximate model of the linearized SWE. Our approach was based on a simplified model of canal hydrodynamics, which captures the influence of both upstream and downstream variations. We presented conditions for the existence of a UIO when failure signals in the state and measurement equations were coupled. These conditions are delay-dependent, and can also incorporate communication network-induced time-delays in the sensor-control data. A residual generation procedure was used to detect and isolate such failure signals.

Furthermore, the performance of the UIO-based FDI scheme was investigated on scenarios when the fault signals in the state and measurement equations were uncoupled. Such scenarios can result from the actions of an attacker which simultaneously compromises sensor-control data and offtakes for the purpose of water pilfering (or even for causing damage to the canal system). For a class of attack scenarios, we also proposed a simple modification of the UIO-based FDI scheme to a threshold-based A/FDI scheme. While practical tuning rules of the proposed A/FDI scheme is a topic of further investigation, an interesting theoretical open question is to adapt these threshold parameters to be sensitive to attacks.

From the viewpoint of cyber-security of canal automation systems, we find that sensor redundancy (i.e., installation of multiple sensors for each candidate fault/attack), and making critical sensors more resilient to manipulation and tampering is a reasonable cyber-defense strategy. For example, for the cases when offtake withdrawals are located near the downstream end, the downstream level sensors are more critical for successful isolation of failures and hence, more investment should be made to make them tamper resistant.

When the compromise of sensor measurements was restricted to a given pool, the diagnosis of faults that are local to the pool is the most severely affected. The effect was also propagated to neighboring pools, although to a lesser extent. However, when sensor measurements from multiple

[5]In this case, the problem becomes a dynamic game between the attacker and the diagnostic scheme, where the informational assumptions become crucial. Such a game theoretic analysis is outside the scope of our work.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

pools were compromised by a strategic and resourceful attacker, the F/ADI scheme can result in an incorrect diagnosis (or even perfect stealthiness). Thus, priority should be placed on reducing the chance of multiple and coordinated compromises.

Finally, we believed that the insights presented in this paper motivates further investigation of novel model-based attack diagnostic schemes, which are not based on the assumptions made by classical FDI schemes (i.e., the assumption of nonsimultaneous failure signals). From our analysis we concluded that a proper selection of internal model, and increased emphasis on securing critical sensor measurements could lead to better performance of F/ADI schemes under deception attacks. Such attack-sensitive diagnostic schemes will also assist in the development of automatic control strategies, which are resilient to a broad class of physical faults and cyber-attack signals.

APPENDIX

Proof of Proposition 3: Under (28), we note that $\bar{Z}_i$ defined in (29) satisfies $\bar{Z}_i > 0$, $i = 1, \ldots, 4$. Inspired by the work of Lin *et al.* [14], under (27) and $P > 0$, we consider the following Lyapunov–Krasovskii functional:

$$V(\mathrm{e}(t)) = \mathrm{e}(t)^{\mathsf{T}} P \mathrm{e}(t) + \sum_{i=1}^{4} \int_{t-\tau_i(t)}^{t} \begin{pmatrix} \mathrm{e}(s) \\ \dot{\mathrm{e}}(s) \end{pmatrix}^{\mathsf{T}} \begin{pmatrix} Q_i & U_i \\ U_i^{\mathsf{T}} & R_i \end{pmatrix} \begin{pmatrix} \mathrm{e}(s) \\ \dot{\mathrm{e}}(s) \end{pmatrix} ds + \sum_{i=1}^{4} \int_{0}^{h_i} \int_{t-\theta}^{t} \begin{pmatrix} \mathrm{e}(s) \\ \dot{\mathrm{e}}(s) \end{pmatrix}^{\mathsf{T}} \begin{pmatrix} S_i & W_i \\ W_i^{\mathsf{T}} & Z_i \end{pmatrix} \begin{pmatrix} \mathrm{e}(s) \\ \dot{\mathrm{e}}(s) \end{pmatrix} ds\, d\theta. \quad (37)$$

Let us define the following vectors:

$$\eta(t)^{\mathsf{T}} := \left(\tilde{\mathrm{e}}(t)^{\mathsf{T}} \tilde{\dot{\mathrm{e}}}(t)^{\mathsf{T}}\right) \quad \zeta(s)^{\mathsf{T}} := \left(\mathrm{e}(s)^{\mathsf{T}}, \dot{\mathrm{e}}(s)^{\mathsf{T}}\right)$$

where

$$\tilde{\mathrm{e}}(t)^{\mathsf{T}} := \left(\mathrm{e}(t)^{\mathsf{T}}, \mathrm{e}(t-\tau_1(t))^{\mathsf{T}}, \ldots, \mathrm{e}(t-\tau_4(t))^{\mathsf{T}}\right)$$
$$\tilde{\dot{\mathrm{e}}}(t)^{\mathsf{T}} := \left(\dot{\mathrm{e}}(t)^{\mathsf{T}}, \dot{\mathrm{e}}(t-\tau_1(t))^{\mathsf{T}}, \ldots, \dot{\mathrm{e}}(t-\tau_4(t))^{\mathsf{T}}\right).$$

We make the following two observations. First, using the Leibnitz rule

$$\sum_{i=1}^{4} \mathrm{e}(t-\tau_i(t)) = 4\mathrm{e}(t) - \sum_{i=1}^{4} \int_{t-\tau_i(t)}^{t} \dot{\mathrm{e}}(s) ds$$

we obtain for any matrices H_i, with appropriate dimensions, and $i = 0, \ldots, 9$

$$0 = 2\left(\sum_{i=0}^{4} \mathrm{e}(t-\tau_i(t))^{\mathsf{T}} H_i + \sum_{i=5}^{9} \dot{\mathrm{e}}(t-\tau_i(t))^{\mathsf{T}} H_i\right) \times \left(4\mathrm{e}(t) - \sum_{i=1}^{4} \mathrm{e}(t-\tau_i(t)) - \sum_{i=1}^{4} \int_{t-\tau_i(t)}^{t} \dot{\mathrm{e}}(s) ds\right) \quad (38)$$

or equivalently

$$0 = 2\eta(t)^{\mathsf{T}} H \Delta_1 \eta(t) - 2\sum_{i=1}^{4} \int_{t-\tau_i(t)}^{t} \eta(t)^{\mathsf{T}} \begin{pmatrix} 0 \\ H^{\mathsf{T}} \end{pmatrix}^{\mathsf{T}} \zeta(s) ds \quad (39)$$

where

$$H^{\mathsf{T}} := \left(H_0^{\mathsf{T}}\ H_1^{\mathsf{T}}\ \ldots\ H_9^{\mathsf{T}}\right)$$
$$\Delta_1 := \left(4\ -1\ -1\ -1\ -1\ 0\ 0\ 0\ 0\ 0\right).$$

Second, using $\sum_{i=0}^{4} F_i \mathrm{e}(t-\tau_i) - \dot{\mathrm{e}}(t) = 0$, we obtain for a matrix P with appropriate dimensions and scalars $\epsilon_0, \ldots, \epsilon_9$, $\bar{\epsilon}_1, \ldots, \bar{\epsilon}_4$

$$0 = 2\left(\sum_{i=0}^{4} \mathrm{e}(t-\tau_i(t))^{\mathsf{T}} \epsilon_i + \sum_{i=5}^{9} \dot{\mathrm{e}}(t-\tau_i(t))^{\mathsf{T}} \epsilon_i + \sum_{i=1}^{4} \int_{t-\tau_i(t)}^{t} \mathrm{e}^{\mathsf{T}}(s) ds \bar{\epsilon}_i\right) P \times \left(\sum_{i=0}^{4} F_i \mathrm{e}(t-\tau_i) - \dot{\mathrm{e}}(t)\right) \quad (40)$$

or equivalently

$$0 = 2\eta(t)^{\mathsf{T}} \Upsilon \Delta_2 \eta(t) - 2\sum_{i=1}^{4} \int_{t-\tau_i(t)}^{t} \eta(t) \left(-\bar{\epsilon}_i \Delta_2^{\mathsf{T}} P^{\mathsf{T}}\ \ 0\right) \zeta(s) ds \quad (41)$$

where

$$\Upsilon^{\mathsf{T}} := P^{\mathsf{T}} \left(\epsilon_0\ \epsilon_1\ \ldots\ \epsilon_9\right)$$
$$\Delta_2 := \left(F_0\ \ldots\ F_4\ -I\ 0\ 0\ 0\ 0\right).$$

Adding (39) and (41) to the time derivative of $V(\mathrm{e}(t))$ along the solution of (21), we can write

$$\begin{aligned}\dot{V}(\mathrm{e}(t)) = {} & 2\mathrm{e}(t)^{\mathsf{T}} P \dot{\mathrm{e}}(t) + \sum_{i=1}^{4} \begin{pmatrix} \mathrm{e}(t) \\ \\ \dot{\mathrm{e}}(t) \end{pmatrix}^{\mathsf{T}} \\ & \times \begin{pmatrix} Q_i & U_i \\ U_i^{\mathsf{T}} & R_i \end{pmatrix} \begin{pmatrix} \mathrm{e}(t) \\ \dot{\mathrm{e}}(t) \end{pmatrix} - \sum_{i=1}^{4} (1 - \dot{\tau}_i(t)) \\ & \times \begin{pmatrix} \mathrm{e}(t-\tau_i(t)) \\ \dot{\mathrm{e}}(t-\tau_i(t)) \end{pmatrix}^{\mathsf{T}} \begin{pmatrix} Q_i & U_i \\ U_i^{\mathsf{T}} & R_i \end{pmatrix} \begin{pmatrix} \mathrm{e}(t-\tau_i(t)) \\ \dot{\mathrm{e}}(t-\tau_i(t)) \end{pmatrix} \\ & + \sum_{i=1}^{4} h_i \begin{pmatrix} \mathrm{e}(t) \\ \dot{\mathrm{e}}(t) \end{pmatrix}^{\mathsf{T}} \begin{pmatrix} S_i & W_i \\ W_i^{\mathsf{T}} & Z_i \end{pmatrix} \begin{pmatrix} \mathrm{e}(t) \\ \dot{\mathrm{e}}(t) \end{pmatrix} \\ & - \sum_{i=1}^{4} \int_{t-h_i(t)}^{t} \begin{pmatrix} \mathrm{e}(s) \\ \dot{\mathrm{e}}(s) \end{pmatrix}^{\mathsf{T}} \begin{pmatrix} S_i & W_i \\ W_i^{\mathsf{T}} & Z_i \end{pmatrix} \begin{pmatrix} \mathrm{e}(s) \\ \dot{\mathrm{e}}(s) \end{pmatrix} ds \\ & + 2\eta(t)^{\mathsf{T}} [H \Delta_1 + \Upsilon \Delta_2] \eta(t) \\ & - 2\sum_{i=1}^{4} \int_{t-h_i(t)}^{t} \eta(t)^{\mathsf{T}} \bar{H}_i \zeta(s) ds \\ & + \sum_{i=1}^{4} \Bigg(\tau_i(t) \eta(t)^{\mathsf{T}} \bar{H}_i \bar{Z}_i \bar{H}_i^{\mathsf{T}} \eta(t) \\ & - \int_{t-\tau_i(t)}^{t} \eta(t)^{\mathsf{T}} \bar{H}_i \bar{Z}_i \bar{H}_i^{\mathsf{T}} \eta(t) ds\Bigg) \end{aligned} \quad (42)$$

where $\bar{Z}_i$ and $\bar{H}_i$ are given by

$$\bar{Z}_i := \begin{pmatrix} S_i & W_i \\ W_i^\top & Z_i \end{pmatrix}$$

$$\bar{H}_i := \begin{pmatrix} -\bar{\epsilon}_i(PF_0)^\top & H_0 \\ -\bar{\epsilon}_i(PF_1)^\top & H_1 \\ -\bar{\epsilon}_i(PF_2)^\top & H_2 \\ -\bar{\epsilon}_i(PF_3)^\top & H_3 \\ -\bar{\epsilon}_i(PF_4)^\top & H_4 \\ \bar{\epsilon}_i P^\top & H_5 \\ 0 & H_6 \\ 0 & H_7 \\ 0 & H_8 \\ 0 & H_9 \end{pmatrix}$$

for $i = 1, 2, 3, 4$. Using the fact that $\tau_i(t) \leqslant h_i$, and $\dot{\tau}_i(t) \leqslant d_i < 1$, for $i = 1, 2, 3, 4$

$$\dot{V}(\mathrm{e}(t)) \leqslant \eta(t)^\top \left(\Phi + \sum_{i=1}^{4} h_i \bar{H}_i \bar{Z}_i^{-1} \bar{H}_i^\top \right) \eta(t) - \sum_{i=1}^{4} \int_{t-h_i(t)}^{t} \Gamma_i(t,s)^\top \bar{Z}_i^{-1} \Gamma_i(t,s) ds \quad (43)$$

where $\Gamma_i(t,s) := (\bar{H}_i^\top \eta(t) + \bar{Z}_i \zeta(s))$, and the matrix $\Phi = (\phi_{jk})$ represented as

$$\begin{pmatrix} \phi_{00} & \phi_{01} & \phi_{02} & \phi_{03} & \phi_{04} & \phi_{05} & \phi_{06} & \phi_{07} & \phi_{08} & \phi_{09} \\ * & \phi_{11} & \phi_{12} & \phi_{13} & \phi_{14} & \phi_{15} & \phi_{16} & \phi_{17} & \phi_{18} & \phi_{19} \\ * & * & \phi_{22} & \phi_{23} & \phi_{24} & \phi_{25} & \phi_{26} & \phi_{27} & \phi_{28} & \phi_{29} \\ * & * & * & \phi_{33} & \phi_{34} & \phi_{35} & \phi_{36} & \phi_{37} & \phi_{38} & \phi_{39} \\ * & * & * & * & \phi_{44} & \phi_{45} & \phi_{46} & \phi_{47} & \phi_{48} & \phi_{49} \\ * & * & * & * & * & \phi_{55} & \phi_{56} & \phi_{57} & \phi_{58} & \phi_{59} \\ * & * & * & * & * & * & \phi_{66} & \phi_{67} & \phi_{68} & \phi_{69} \\ * & * & * & * & * & * & * & \phi_{77} & \phi_{78} & \phi_{79} \\ * & * & * & * & * & * & * & * & \phi_{88} & \phi_{89} \\ * & * & * & * & * & * & * & * & * & \phi_{99} \end{pmatrix} \quad (44)$$

with block elements ϕ_{jk} given by

$$\phi_{00} = \sum_{i=1}^{4}(Q_i + h_i S_i) + \epsilon_0 \operatorname{sym}(PF_0) + 4\operatorname{sym}(H_0)$$
$$\phi_{01} = \epsilon_0 PF_1 + \epsilon_1(PF_0)^\top + 4H_1^\top - H_0$$
$$\phi_{02} = \epsilon_0 PF_2 + \epsilon_2(PF_0)^\top + 4H_2^\top - H_0$$
$$\phi_{03} = \epsilon_0 PF_3 + \epsilon_3(PF_0)^\top + 4H_3^\top - H_0$$
$$\phi_{04} = \epsilon_0 PF_4 + \epsilon_4(PF_0)^\top + 4H_4^\top - H_0$$
$$\phi_{05} = P + \sum_{i=1}^{4}(U_i + h_i W_i) - \epsilon_0 P + \epsilon_5(PF_0)^\top + 4H_5^\top$$
$$\phi_{06} = \epsilon_6(PF_0)^\top + 4H_6^\top$$
$$\phi_{07} = \epsilon_7(PF_0)^\top + 4H_7^\top$$
$$\phi_{08} = \epsilon_8(PF_0)^\top + 4H_8^\top$$
$$\phi_{09} = \epsilon_9(PF_0)^\top + 4H_9^\top$$
$$\phi_{11} = \epsilon_1 \operatorname{sym}(PF_1) - (1-d_1)Q_1 - \operatorname{sym}(H_1)$$
$$\phi_{12} = \epsilon_1 PF_2 + \epsilon_2(PF_1)^\top - H_1 - H_2^\top$$
$$\phi_{13} = \epsilon_1 PF_3 + \epsilon_3(PF_1)^\top - H_1 - H_3^\top$$
$$\phi_{14} = \epsilon_1 PF_4 + \epsilon_4(PF_1)^\top - H_1 - H_4^\top$$
$$\phi_{15} = -\epsilon_1 P + \epsilon_5(PF_1)^\top - H_5^\top$$
$$\phi_{16} = +\epsilon_6(PF_1)^\top - (1-d_1)U_1 - H_6^\top$$
$$\phi_{17} = +\epsilon_7(PF_1)^\top - H_7^\top$$
$$\phi_{18} = +\epsilon_8(PF_1)^\top - H_8^\top$$
$$\phi_{19} = +\epsilon_9(PF_1)^\top - H_9^\top$$
$$\phi_{22} = +\epsilon_2 \operatorname{sym}(PF_2) - (1-d_2)Q_2 - \operatorname{sym}(H_2)$$
$$\phi_{23} = +\epsilon_2 PF_3 + \epsilon_3(PF_2)^\top - H_2 - H_3^\top$$
$$\phi_{24} = +\epsilon_2 PF_4 + \epsilon_4(PF_2)^\top - H_2 - H_4^\top$$
$$\phi_{25} = -\epsilon_2 P + \epsilon_5(PF_2)^\top - H_5^\top$$
$$\phi_{26} = +\epsilon_6(PF_2)^\top - H_6^\top$$
$$\phi_{27} = -(1-d_2)U_2 + \epsilon_7(PF_2)^\top - H_7^\top$$
$$\phi_{28} = +\epsilon_8(PF_2)^\top - H_8^\top$$
$$\phi_{29} = +\epsilon_9(PF_2)^\top - H_9^\top$$
$$\phi_{33} = -(1-d_3)Q_3 + \epsilon_3 \operatorname{sym}(PF_3) - \operatorname{sym}(H_3)$$
$$\phi_{34} = +\epsilon_3 PF_4 + \epsilon_4(PF_3)^\top - H_3 - H_4^\top$$
$$\phi_{35} = -\epsilon_3 P + \epsilon_5(PF_3)^\top - H_5^\top$$
$$\phi_{36} = +\epsilon_6(PF_3)^\top - H_6^\top$$
$$\phi_{37} = +\epsilon_7(PF_3)^\top - H_7^\top$$
$$\phi_{38} = +\epsilon_8(PF_3)^\top - (1-d_3)U_3 - H_8^\top$$
$$\phi_{39} = +\epsilon_9(PF_3)^\top - H_9^\top$$
$$\phi_{44} = -(1-d_4)Q_4 + \epsilon_4 \operatorname{sym}(PF_4)^\top - \operatorname{sym}(H_4)$$
$$\phi_{45} = -\epsilon_4 P + \epsilon_5(PF_4)^\top - H_5^\top$$
$$\phi_{46} = +\epsilon_6(PF_4)^\top - H_6^\top$$
$$\phi_{47} = +\epsilon_7(PF_4)^\top - H_7^\top$$
$$\phi_{48} = +\epsilon_8(PF_4)^\top - H_8^\top$$
$$\phi_{49} = -(1-d_4)U_4 + \epsilon_9(PF_4)^\top - H_9^\top$$
$$\phi_{55} = \sum_{i=1}^{4}(R_i + h_i Z_i) - \epsilon_5 \operatorname{sym}(P)$$
$$\phi_{56} = -\epsilon_6 P^\top$$
$$\phi_{57} = -\epsilon_7 P^\top$$
$$\phi_{58} = -\epsilon_8 P^\top$$
$$\phi_{59} = -\epsilon_9 P^\top$$
$$\phi_{66} = -(1-d_1)R_1$$
$$\phi_{67} = 0$$
$$\phi_{68} = 0$$
$$\phi_{69} = 0$$
$$\phi_{77} = -(1-d_2)R_2$$

$$\phi_{78} = 0$$
$$\phi_{79} = 0$$
$$\phi_{88} = -(1-d_3)R_3$$
$$\phi_{89} = 0$$
$$\phi_{99} = -(1-d_4)R_4$$

where $\mathrm{sym}(M) := M + M^{\mathsf{T}}$. From (43), we see that if $\left(\Phi + \sum_{i=1}^{4} h_i \bar{H}_i \bar{Z}_i^{-1} \bar{H}_i^{\mathsf{T}}\right) < 0$ (equivalently, using Schur complements if LMI (28) holds), then $\dot{V}(\mathrm{e}(t)) < 0$. Following stability theory of delay differential equations [28], the error dynamic (26) is asymptotically stable. Using (25) and defining $U := PK$, we obtain $\bar{H}_i$. ■

Finally, from (25) and using $U = PK$, we obtain ϕ_{jk}

$$\phi_{00} = \sum_{i=1}^{4}(Q_i + h_i S_i) + \epsilon_0\,\mathrm{sym}(P\chi_0 - U\beta_0) + 4\,\mathrm{sym}(H_0)$$
$$\phi_{01} = \epsilon_0(P\chi_1 - U\beta_1) + \epsilon_1(P\chi_0 - U\beta_0)^{\mathsf{T}} + 4H_1^{\mathsf{T}} - H_0$$
$$\phi_{02} = \epsilon_0(P\chi_2 - U\beta_2) + \epsilon_2(P\chi_0 - U\beta_0)^{\mathsf{T}} + 4H_2^{\mathsf{T}} - H_0$$
$$\phi_{03} = \epsilon_0(P\chi_3 - U\beta_3) + \epsilon_3(P\chi_0 - U\beta_0)^{\mathsf{T}} + 4H_3^{\mathsf{T}} - H_0$$
$$\phi_{04} = \epsilon_0(P\chi_4 - U\beta_4) + \epsilon_4(P\chi_0 - U\beta_0)^{\mathsf{T}} + 4H_4^{\mathsf{T}} - H_0$$
$$\phi_{05} = P + \sum_{i=1}^{4}(U_i + h_i W_i) - \epsilon_0 P + \epsilon_5(P\chi_0 - U\beta_0)^{\mathsf{T}} + 4H_5^{\mathsf{T}}$$
$$\phi_{06} = \epsilon_6(P\chi_0 - U\beta_0)^{\mathsf{T}} + 4H_6^{\mathsf{T}}$$
$$\phi_{07} = \epsilon_7(P\chi_0 - U\beta_0)^{\mathsf{T}} + 4H_7^{\mathsf{T}}$$
$$\phi_{08} = \epsilon_8(P\chi_0 - U\beta_0)^{\mathsf{T}} + 4H_8^{\mathsf{T}}$$
$$\phi_{09} = \epsilon_9(P\chi_0 - U\beta_0)^{\mathsf{T}} + 4H_9^{\mathsf{T}}$$
$$\phi_{11} = \epsilon_1\,\mathrm{sym}(P\chi_1 - U\beta_1) - (1-d_1)Q_1 - \mathrm{sym}(H_1)$$
$$\phi_{12} = \epsilon_1(P\chi_2 - U\beta_2) + \epsilon_2(P\chi_1 - U\beta_1)^{\mathsf{T}} - H_1 - H_2^{\mathsf{T}}$$
$$\phi_{13} = \epsilon_1(P\chi_3 - U\beta_3) + \epsilon_3(P\chi_1 - U\beta_1)^{\mathsf{T}} - H_1 - H_3^{\mathsf{T}}$$
$$\phi_{14} = \epsilon_1(P\chi_4 - U\beta_4) + \epsilon_4(P\chi_1 - U\beta_1)^{\mathsf{T}} - H_1 - H_4^{\mathsf{T}}$$
$$\phi_{15} = -\epsilon_1 P + \epsilon_5(P\chi_1 - U\beta_1)^{\mathsf{T}} - H_5^{\mathsf{T}}$$
$$\phi_{16} = +\epsilon_6(P\chi_1 - U\beta_1)^{\mathsf{T}} - (1-d_1)U_1 - H_6^{\mathsf{T}}$$
$$\phi_{17} = +\epsilon_7(P\chi_1 - U\beta_1)^{\mathsf{T}} - H_7^{\mathsf{T}}$$
$$\phi_{18} = +\epsilon_8(P\chi_1 - U\beta_1)^{\mathsf{T}} - H_8^{\mathsf{T}}$$
$$\phi_{19} = +\epsilon_9(P\chi_1 - U\beta_1)^{\mathsf{T}} - H_9^{\mathsf{T}}$$
$$\phi_{22} = +\epsilon_2\,\mathrm{sym}(P\chi_2 - U\beta_2) - (1-d_2)Q_2 - \mathrm{sym}(H_2)$$
$$\phi_{23} = +\epsilon_2(P\chi_3 - U\beta_3) + \epsilon_3(P\chi_2 - U\beta_2)^{\mathsf{T}} - H_2 - H_3^{\mathsf{T}}$$
$$\phi_{24} = +\epsilon_2(P\chi_4 - U\beta_4) + \epsilon_4(P\chi_2 - U\beta_2)^{\mathsf{T}} - H_2 - H_4^{\mathsf{T}}$$
$$\phi_{25} = -\epsilon_2 P + \epsilon_5(P\chi_2 - U\beta_2)^{\mathsf{T}} - H_5^{\mathsf{T}}$$
$$\phi_{26} = +\epsilon_6(P\chi_2 - U\beta_2)^{\mathsf{T}} - H_6^{\mathsf{T}}$$
$$\phi_{27} = -(1-d_2)U_2 + \epsilon_7(P\chi_2 - U\beta_2)^{\mathsf{T}} - H_7^{\mathsf{T}}$$
$$\phi_{28} = +\epsilon_8(P\chi_2 - U\beta_2)^{\mathsf{T}} - H_8^{\mathsf{T}}$$
$$\phi_{29} = +\epsilon_9(P\chi_2 - U\beta_2)^{\mathsf{T}} - H_9^{\mathsf{T}}$$
$$\phi_{33} = -(1-d_3)Q_3 + \epsilon_3\,\mathrm{sym}(P\chi_3 - U\beta_3) - \mathrm{sym}(H_3)$$
$$\phi_{34} = +\epsilon_3(P\chi_4 - U\beta_4) + \epsilon_4(P\chi_3 - U\beta_3)^{\mathsf{T}} - H_3 - H_4^{\mathsf{T}}$$
$$\phi_{35} = -\epsilon_3 P + \epsilon_5(P\chi_3 - U\beta_3)^{\mathsf{T}} - H_5^{\mathsf{T}}$$
$$\phi_{36} = +\epsilon_6(P\chi_3 - U\beta_3)^{\mathsf{T}} - H_6^{\mathsf{T}}$$
$$\phi_{37} = +\epsilon_7(P\chi_3 - U\beta_3)^{\mathsf{T}} - H_7^{\mathsf{T}}$$
$$\phi_{38} = +\epsilon_8(P\chi_3 - U\beta_3)^{\mathsf{T}} - (1-d_3)U_3 - H_8^{\mathsf{T}}$$
$$\phi_{39} = +\epsilon_9(P\chi_3 - U\beta_3)^{\mathsf{T}} - H_9^{\mathsf{T}}$$
$$\phi_{44} = -(1-d_4)Q_4 + \epsilon_4\,\mathrm{sym}(P\chi_4 - U\beta_4)^{\mathsf{T}} - \mathrm{sym}(H_4)$$
$$\phi_{45} = -\epsilon_4 P + \epsilon_5(P\chi_4 - U\beta_4)^{\mathsf{T}} - H_5^{\mathsf{T}}$$
$$\phi_{46} = +\epsilon_6(P\chi_4 - U\beta_4)^{\mathsf{T}} - H_6^{\mathsf{T}}$$
$$\phi_{47} = +\epsilon_7(P\chi_4 - U\beta_4)^{\mathsf{T}} - H_7^{\mathsf{T}}$$
$$\phi_{48} = +\epsilon_8(P\chi_4 - U\beta_4)^{\mathsf{T}} - H_8^{\mathsf{T}}$$
$$\phi_{49} = -(1-d_4)U_4 + \epsilon_9(P\chi_4 - U\beta_4)^{\mathsf{T}} - H_9^{\mathsf{T}}$$
$$\phi_{55} = \sum_{i=1}^{4}(R_i + h_i Z_i) - \epsilon_5\,\mathrm{sym}(P)$$
$$\phi_{56} = -\epsilon_6 P^{\mathsf{T}}$$
$$\phi_{57} = -\epsilon_7 P^{\mathsf{T}}$$
$$\phi_{58} = -\epsilon_8 P^{\mathsf{T}}$$
$$\phi_{59} = -\epsilon_9 P^{\mathsf{T}}$$
$$\phi_{66} = -(1-d_1)R_1$$
$$\phi_{67} = 0$$
$$\phi_{68} = 0$$
$$\phi_{69} = 0$$
$$\phi_{77} = -(1-d_2)R_2$$
$$\phi_{78} = 0$$
$$\phi_{79} = 0$$
$$\phi_{88} = -(1-d_3)R_3$$
$$\phi_{89} = 0$$
$$\phi_{99} = -(1-d_4)R_4.$$

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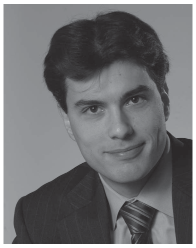

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