2013 European Control Conference (ECC)
July 17-19, 2013, Zürich, Switzerland.

Multiple Sensor Fault Detection and Isolation for Large-scale Interconnected Nonlinear Systems

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Abstract— **This paper presents the design of a methodology for detecting and isolating multiple sensor faults in large-scale interconnected nonlinear systems. For each of the interconnected subsystems, we design a local sensor fault diagnosis (LSFD) agent responsible for multiple sensor fault detection and isolation in the local sensor set. The multiple sensor fault detection is realized through a bank of modules, monitoring smaller groups of sensors that belong to the local sensor set. The detection of faults in sensor groups is conducted using robust analytical redundancy relations, formulated by structured residuals and adaptive thresholds. The isolation of multiple faulty sensors in the local sensor set is realized by integrating the decisions of the LSFD agent's modules and applying a reasoning-based combinatorial decision logic. The simulation example of an automated highway system is used to illustrate the application of the multiple SFDI methodology.**

I. INTRODUCTION

In 2009, an Airbus 330-203 operated by Air France was crashed into the Atlantic ocean, killing all 228 passengers and air crew. According to the investigation report [1], all three speed sensors became faulty (transient fault), causing the disconnection of the autopilot, while their faulty readings caused the pilots to apply inappropriate actions, which resulted in the accident. The findings of this report raise the need for applying sensor fault diagnosis mechanisms, capable of detecting, isolating and if possible, estimating multiple sensor faults.

Sensor fault detection and isolation (SFDI) methods are classified into physical redundancy- and model-based methods. When the physical redundancy approach is not practical due to high cost of installation and maintenance, and due to space restrictions, model-based techniques can be used [2]. These techniques are further categorized as quantitative or qualitative methods [3], [4]; the first category relies on a nominal mathematical model describing the system, while the second one uses symbolic and/or qualitative system representations.

Quantitative model-based approaches such as parity equations and observers [5], [6] are widely used for SFDI. These approaches have been mostly adopted by the FDI community, which elaborates on making them robust with respect to modeling errors, noise and system disturbances. Among them, the observer-based approaches are used for the development of SFDI methodologies for nonlinear systems. In order to address the problem of multiple sensor faults, several researchers have designed SFDI methods based on a single nonlinear observer or a bank of observers [7]–[10], which can further be combined with the utilization of fault signature matrices [11]. However, there are very few observer-based SFDI methodologies for interconnected nonlinear systems even for single sensor fault occurrence in one of the subsystems [12], while, to the authors' best knowledge, the work in this paper is the first to develop an observer-based SFDI technique tackling the problem of multiple sensor faults.

Qualitative model-based techniques are typically used by the artificial intelligence diagnostic (DX) community [13]. The design of these techniques is based on the utilization of either causal models, such as signed digraphs, bond graphs, fault trees etc. [14], [15], or abstraction hierarchies that can be either functional or structural [16], [17]. The nature of models, which do not use analytical mathematical expressions, facilitates the application of the qualitative model-based methods to large-scale systems. The DX community considers fault detection and isolation as a unified problem and exploits reasoning techniques for enhancing fault isolation, thereby facilitating multiple sensor fault isolation [18]. Several researchers have analyzed the equivalence and differences between the quantitative and qualitative methods, whilst they have designed a unified framework exploiting the assets of each approach [19], [20].

The objective of this work is the design of a model-based methodology for detecting and isolating multiple sensor faults occurring in interconnected, nonlinear systems. For each of the interconnected subsystems, we design a dedicated local sensor fault diagnosis (LSFD) agent, tailored to detect the presence of faults in the local set of sensors used for monitoring and control of the underlying subsystem, and isolate the faulty sensors in this set. The LSFD agents are deployed in a decentralized framework, in which there is no information exchange. The design of the LSFD agent relies on the decomposition of the local sensor set into smaller groups of sensors. Then, a module is built up for monitoring each group of sensors, whose main task is to detect the occurrence of sensor faults in the group. The detection is realized by checking if analytical redundancy relations (ARRs), formulated by residuals and adaptive thresholds, are not satisfied. The utilization of the bank of modules is the first stage of multiple sensor fault isolation, which is further enhanced through the integration and combinatorial process of the decisions obtained by the modules.

This paper is organized as follows. The problem formulation along with the design assumptions are described in

The research leading to these results has received funding from the European Union Seventh Framework Programme [FP7/2007-2013] under Grant Agreement n° 270428.

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Section II. The architecture of the proposed multiple SFDI methodology for nonlinear interconnected systems is presented in Section III. The design of the modules in a LSFD agent and the multiple sensor fault isolation decision logic are provided in Sections IV and V. The application of the proposed SFDI architecture to an automated highway system is illustrated in Section VI, followed by some concluding remarks in Section VII.

II. Problem Formulation

Consider a large-scale, nonlinear uncertain system that is comprised of N interconnected nonlinear subsystems. The I-th subsystem, $I \in \{1,\dots,N\}$, denoted as $\Sigma^{(I)}$, is described by:

$$\Sigma^{(I)}: \quad \dot{x}^{(I)}(t) = A^{(I)}x^{(I)}(t) + \gamma^{(I)}(x^{(I)}(t), u^{(I)}(t)) + h^{(I)}(x^{(I)}(t), u^{(I)}(t), z^{(I)}(t)) + \eta^{(I)}(x^{(I)}(t), u^{(I)}(t), t), \tag{1}$$

where $x^{(I)} \in \mathbb{R}^{n_I}$, $u^{(I)} \in \mathbb{R}^{\ell_I}$ are the state and input vector of $\Sigma^{(I)}$, respectively, while $z^{(I)} \in \mathbb{R}^{p_I}$ is the interconnection vector containing states of the neighboring subsystems of $\Sigma^{(I)}$. The constant matrix $A^{(I)} \in \mathbb{R}^{n_I \times n_I}$ is the linearized part of the state equation, $\gamma^{(I)}: \mathbb{R}^{n_I} \times \mathbb{R}^{\ell_I} \mapsto \mathbb{R}^{n_I}$ represents the nonlinear dynamics, $h^{(I)}: \mathbb{R}^{n_I} \times \mathbb{R}^{\ell_I} \times \mathbb{R}^{p_I} \mapsto \mathbb{R}^{n_I}$ represents the interconnection dynamics, and $\eta^{(I)}: \mathbb{R}^{n_I} \times \mathbb{R}^{\ell_I} \times \mathbb{R} \in \mathbb{R}^{n_I}$ denotes the modeling uncertainty of $\Sigma^{(I)}$. The input vector $u^{(I)}$ is generated by a feedback control algorithm using sensor measurements and possibly some desired reference signals.

The sensors that are used for monitoring and control of $\Sigma^{(I)}$, constitute a local sensor set $\mathcal{S}^{(I)} = \{\mathcal{S}^{(I)}\{1\}, \dots, \mathcal{S}^{(I)}\{m_I\}\}$, $I \in \{1,\dots,N\}$, where $\mathcal{S}^{(I)}\{j\}$, $j \in \{1,\dots,m_I\}$ denotes the j-th sensor. The I-th local sensor set is described by

$$\mathcal{S}^{(I)}: \quad y^{(I)}(t) = C^{(I)}x^{(I)}(t) + d^{(I)}(t) + f^{(I)}(t). \tag{2}$$

where $y^{(I)} \in \mathbb{R}^{m_I}$ is the sensor output vector, $d^{(I)} \in \mathbb{R}^{m_I}$ denotes the noise vector corrupting the measurements of $\mathcal{S}^{(I)}$ and $f^{(I)} \in \mathbb{R}^{m_I}$ represents the possible sensor fault vector. The j-th sensor is characterized by

$$\mathcal{S}^{(I)}\{j\}: \quad y_j^{(I)}(t) = C_j^{(I)}x^{(I)}(t) + d_j^{(I)}(t) + f_j^{(I)}(t). \tag{3}$$

The sensor output vector can be affected by multiple faults, given that the j-th output $y_j^{(I)}$ is changed due to a single fault in the j-th sensor, modeled as $f_j^{(I)}(t)$, which occurs at $T_{f_j}^{(I)}$, $j \in \{1,\dots,m_I\}$, i.e. $f_j^{(I)}(t) = 0$ for all $t < T_{f_j}^{(I)}$.

The objective of this work is to design a methodology for detecting the presence of sensor faults that may occur in more than one subsystems, taking into account the following assumptions:

Assumption 1: For each subsystem $I \in \{1,\dots,N\}$, the state vector $x^{(I)}$ and input vector $u^{(I)}$ generated by a feedback controller, remain bounded before and after the occurrence of multiple sensor faults; i.e., there exist compact regions of stability $\mathcal{U}_I \subset \mathbb{R}^{\ell_I}$, $\mathcal{X}_I \subset \mathbb{R}^{n_I}$ such that $\left(x^{(I)}(t), u^{(I)}(t)\right) \in \mathcal{X}_I \times \mathcal{U}_I$, for all $t > 0$.

Assumption 2: The nonlinear vector field $\gamma^{(I)}$ is locally Lipschitz in $x^{(I)} \in \mathcal{X}_I$, for all $u^{(I)} \in \mathcal{U}_I$ and $t > 0$, while $h^{(I)}$ is locally Lipschitz in $x^{(I)} \in \mathcal{X}_I$ and $z^{(I)} \in \mathcal{Z}_I$, for all $u^{(I)} \in \mathcal{U}_I$ and $t > 0$. The vector space $\mathcal{Z}_I \subset \mathbb{R}^{p_I}$ denotes a compact region of stability within which $z^{(I)}$ reside.

Assumption 3: The unknown modeling uncertainty of the (I)-subsystem $\eta^{(I)}(x^{(I)}(t), u^{(I)}(t), t)$ is bounded by a known functional $\bar{\eta}^{(I)}$ for all $x^{(I)} \in \mathcal{X}_I$, $u^{(I)} \in \mathcal{U}_I$ and $t > 0$; i.e. $\left|\eta^{(I)}(x^{(I)}(t), u^{(I)}(t), t)\right| \leq \bar{\eta}^{(I)}(x^{(I)}(t), u^{(I)}(t), t)$, whereas the known functional $\bar{\eta}^{(I)}$ is locally Lipschitz in $x^{(I)} \in \mathcal{X}_I$, for all $u^{(I)} \in \mathcal{U}_I$ and $t > 0$.

Assumption 4: The noise corrupting the measurements of each sensor in $\mathcal{S}^{(I)}$ is unknown but uniformly bounded, i.e. $\left|d_i^{(I)}(t)\right| \leq \bar{d}_i^{(I)}$, $i \in \{1,\dots,m_I\}$, where $\bar{d}_i^{(I)}$ is a known constant bound.

III. Multiple SFDI Architecture

This section provides the overall design methodology for detecting and isolating multiple sensor faults occurring in interconnected nonlinear systems. The first step is to design a local sensor fault diagnosis (LSFD) agent, denoted as $\mathcal{M}^{(I)}$, $I \in \{1,\dots,N\}$. The agent $\mathcal{M}^{(I)}$ has access only to the input and output data of the underlying subsystem $\Sigma^{(I)}$ and may use some prior information related to the reference signals of its neighboring subsystems [21], while it does not exchange any information with its neighboring agents. The design of the agent $\mathcal{M}^{(I)}$ is realized as follows; initially, the local sensor set $\mathcal{S}^{(I)}$ is decomposed into N_I groups of sensors. These groups of sensors may be disjoint or overlapping; i.e., some sensors may belong to more than one sensor groups. Each group of sensors, denoted as $\mathcal{S}^{(I,q)}$, consists of $m_{I,q}$ sensors of $\mathcal{S}^{(I)}$ and is characterized by the output vector $y^{(I,q)} \in \mathbb{R}^{m_{I,q}}$; i.e.

$$\mathcal{S}^{(I,q)}: \; y^{(I,q)}(t) = C^{(I,q)}x^{(I)}(t) + d^{(I,q)}(t) + f^{(I,q)}(t), \tag{4}$$

where $C^{(I,q)} \in \mathbb{R}^{m_{I,q} \times n_I}$ and $d^{(I,q)}$, $f^{(I,q)} \in \mathbb{R}^{m_{I,q}}$. The matrix $C^{(I,q)}$ is made up of $m_{I,q}$ rows of $C^{(I)}$ and $y^{(I,q)}$ represents a column vector made up of $m_{I,q}$ elements of $y^{(I)}$ (correspondingly for $d^{(I,q)}$ and $f^{(I,q)}$).

The next step is the design of N_I modules monitoring the sensor groups. The q-th module, denoted as $\mathcal{M}^{(I,q)}$, $q \in \{1,\dots,N_I\}$, is responsible for detecting sensor faults in $\mathcal{S}^{(I,q)}$. The decision logic for determining the faulty status of $\mathcal{S}^{(I,q)}$ relies on checking whether a set of analytical redundancy relations (ARRs) are satisfied. These relations are formulated using observer-based residuals and adaptive thresholds. The decisions of the modules are then integrated and processed applying a reasoning based decision logic, aiming at isolating multiple sensor faults in $\mathcal{S}^{(I)}$.

The reason for decomposing the local sensor set $\mathcal{S}^{(I)}$ is that, in large-scale systems, $\mathcal{S}^{(I)}$ may include a large number of sensors and it would be difficult, or sometimes unfeasible, to design a single module, which can isolate multiple sensor faults. Hence, by decomposing $\mathcal{S}^{(I)}$ and designing dedicated modules, we aim to initially isolate smaller groups of sensors containing the faulty sensors and then, to isolate multiple faulty sensors based on the combinatorial process of the decisions obtained by the N_I modules. The main criterion for decomposing $\mathcal{S}^{(I)}$ is related to the stability of the observer (observability) used for generating the residuals in $\mathcal{M}^{(I,q)}$; i.e., a group of sensors can be created if the design of a stable observer, which uses the measurements $y^{(I,q)}$ and provides an estimation of them, is feasible.

IV. Multiple Sensor Fault Detection

This section presents in detail the design of the module $\mathcal{M}^{(I,q)}$, $I \in \{1,\ldots,N\}$, $q \in \{1,\ldots,N_I\}$ used for multiple sensor fault detection.

A. Observer-based Residual Generation

The nonlinear observer used in the module $\mathcal{M}^{(I,q)}$, denoted as $\mathcal{N}^{(I,q)}$, is structured as follows:

$$\mathcal{N}^{(I,q)}: \quad \dot{\hat{x}}^{(I,q)}(t) = A^{(I)}\hat{x}^{(I,q)}(t) + \gamma^{(I)}(\hat{x}^{(I,q)}(t), u^{(I)}(t)) + h^{(I)}(\hat{x}^{(I,q)}(t), u^{(I)}(t), z_r^{(I)}(t)) + L^{(I,q)}\left(y^{(I,q)}(t) - C^{(I,q)}\hat{x}^{(I,q)}(t)\right) \quad (5)$$

where $\hat{x}^{(I,q)} \in \mathbb{R}^{n_I}$ denotes the estimation of $x^{(I)}$ based on the sensor measurements $y^{(I,q)}$ ($\hat{x}^{(I,q)}(0) = 0$), $L^{(I,q)} \in \mathbb{R}^{n_I \times m_{I,q}}$ is the observer gain matrix and $z_r^{(I)}$ is a vector that contains the a priori known reference signals of the interconnection variables $z^{(I)}$.

The j-th residual generated in the module $\mathcal{M}^{(I,q)}$ is defined as:

$$\varepsilon_y^{(I,q)}(t) = y_j^{(I)}(t) - C_j^{(I)}\hat{x}^{(I,q)}(t), \qquad j \in \mathcal{J}^{(I,q)} \quad (6)$$

where $\mathcal{J}^{(I,q)}$ is the extraction index set (EIS) related to the group of sensors $\mathcal{S}^{(I,q)}$, defined as $\mathcal{J}^{(I,q)} = \{j : \mathcal{S}^{(I)}\{j\} \in \mathcal{S}^{(I,q)}\}$, where $\mathcal{S}^{(I)}\{j\}$, $j \in \{1,\ldots,m_I\}$, stands for the j-th sensor, which belongs to $\mathcal{S}^{(I)}$.

When there is no sensor faults in the group of sensors $\mathcal{S}^{(I,q)}$, its output vector is described by

$$y_H^{(I,q)}(t) = C^{(I,q)}x^{(I)}(t) + d^{(I,q)}(t). \quad (7)$$

This implies that the observer $\mathcal{N}^{(I,q)}$ conveys a healthy estimation of the state vector $x^{(I)}$, denoted as $\hat{x}_H^{(I,q)}(t)$. Let us define $\varepsilon_{x_H}^{(I,q)}(t) \triangleq x^{(I,q)}(t) - \hat{x}_H^{(I,q)}(t)$ as the state estimation error under healthy conditions; taking into account (1), (5) and (7), we obtain:

$$\dot{\varepsilon}_{x_H}^{(I,q)}(t) = A_L^{(I,q)}\varepsilon_{x_H}^{(I,q)}(t) + \tilde{\gamma}_H^{(I,q)}(t) + \tilde{h}_H^{(I,q)}(t) + \eta^{(I)}(x^{(I)}(t), u^{(I)}(t), t) - L^{(I,q)}d^{(I,q)}(t). \quad (8)$$

where $A_L^{(I,q)} = A^{(I)} - L^{(I,q)}C^{(I,q)}$, $\tilde{\gamma}_H^{(I,q)}(t) = \gamma^{(I)}(x^{(I)}(t), u^{(I)}(t)) - \gamma^{(I)}(\hat{x}_H^{(I,q)}, u^{(I)}(t))$ and $\tilde{h}_H^{(I,q)}(t) = h^{(I)}(x^{(I)}(t), u^{(I)}(t), z^{(I)}(t)) - h^{(I)}(\hat{x}_H^{(I,q)}(t), u^{(I)}(t), z_r^{(I)}(t))$. The stability of the estimation error dynamics is analyzed in the following theorem.

Theorem 4.1: For the observable pair $\left(A^{(I)}, C^{(I,q)}\right)$, if the observer gain $L^{(I,q)}$ is chosen such that: a) the matrix $A_L^{(I,q)}$ is stable, and b) there exist positive constants $\rho^{(I,q)}$, $\xi^{(I,q)}$ such that $\left|e^{A_L^{(I,q)}t}\right| \le \rho^{(I,q)}e^{-\xi^{(I,q)}t}$, and $\xi^{(I,q)} > \Lambda_I\rho^{(I,q)}$, where $\Lambda_I = \lambda_{\gamma_I} + \lambda_{h_I} + \lambda_{\eta_I}$ (λ_{γ_I}, λ_{h_I}, λ_{η_I} are the Lipschitz constants of $\gamma^{(I)}$, $h^{(I)}$ and $\bar{\eta}^{(I)}$, respectively), the state estimation error $\varepsilon_{x_H}^{(I,q)}(t)$ is uniformly bounded; i.e. $|\varepsilon_{x_H}^{(I,q)}(t)| \le Z^{(I,q)}(t)$, defined as:

$$Z^{(I,q)}(t) = E^{(I,q)}(t) + \rho^{(I,q)}\Lambda_I \int_0^t E^{(I,q)}(\tau)e^{-\nu^{(I,q)}(t-\tau)}d\tau \quad (9)$$

with $\nu^{(I,q)} = \xi^{(I,q)} - \rho^{(I,q)}\Lambda_I$ and

$$E^{(I,q)}(t) = \rho^{(I,q)}e^{-\xi^{(I,q)}t}\bar{x}^{(I,q)} + \int_0^t \rho^{(I,q)}e^{-\xi^{(I,q)}(t-\tau)}\Big(\bar{\eta}^{(I)}(\hat{x}^{(I,q)}(\tau), u^{(I)}(\tau), \tau) + \lambda_{h_I}\bar{z}^{(I)}\Big)d\tau + \int_0^t \rho_d^{(I,q)}e^{-\xi_d^{(I,q)}(t-\tau)}\bar{d}^{(I,q)}d\tau. \quad (10)$$

Proof: Consider that: a) $\bar{x}^{(I)}$ is a bound for $\left|x^{(I)}(t)\right|$ such that $\left|x^{(I)}(t)\right| \le \bar{x}^{(I)}$, for all $x^{(I)} \in \mathcal{X}^{(I)}$, b) $\rho_d^{(I,q)}$, $\xi_d^{(I,q)}$ are positive constants such that $\left|e^{A_L^{(I,q)}t}L^{(I,q)}\right| \le \rho_d^{(I,q)}e^{-\xi_d^{(I,q)}t}$, c) $\bar{d}^{(I,q)}$ is a bound for $d^{(I,q)}(t)$ such that $\left|d^{(I,q)}(t)\right| \le \bar{d}^{(I,q)}$, and d) $\bar{z}^{(I)}$ is a constant bound related to the tracking error such that $\lim_{t\to\infty}\left|z^{(I)}(t) - z_r^{(I)}(t)\right| \le \bar{z}^{(I)}$, $\forall\ t > 0$. By bounding the solution of (8) and taking into account the conditions described in Theorem 4.1, it yields

$$\left|\varepsilon_{x_H}^{(I,q)}(t)\right| \le \Phi(t)\bar{x}^{(I,q)} + \int_0^t \rho_d^{(I,q)}e^{-\xi_d^{(I,q)}(t-\tau)}\bar{d}^{(I,q)}d\tau + \int_0^t \Phi(t-\tau)\left(\lambda_{\gamma_I}\left|\varepsilon_{x_H}^{(I,q)}(\tau)\right| + \lambda_{h_I}\left|\begin{bmatrix}\varepsilon_{x_H}^{(I,q)}(\tau)\\ \bar{z}^{(I)}\end{bmatrix}\right| + \bar{\eta}^{(I)}(x^{(I)}(\tau), u^{(I)}(\tau), \tau)\right)d\tau \quad (11)$$

where $\Phi(t) = \rho^{(I,q)}e^{-\xi^{(I,q)}t}$. Based on Assumption 3, $\bar{\eta}$ is locally Lipschitz, leading to $\bar{\eta}^{(I)}(x^{(I)}(t), u^{(I)}(t), t) \le \bar{\eta}^{(I)}(\hat{x}_H^{(I,q)}(t), u^{(I)}(t), t) + \lambda_{\eta_I}\left|\varepsilon_{x_H}^{(I,q)}(t)\right|$. Thus, (11) becomes

$$\left|\varepsilon_{x_H}^{(I,q)}(t)\right| \le E^{(I,q)}(t) + \int_0^t \Lambda_I\Phi(t-\tau)\left|\varepsilon_{x_H}^{(I,q)}(t)\right|d\tau \quad (12)$$

with $E^{(I,q)}$ defined in (10). Applying the Bellman-Grownwall Lemma [22] results in:

$$\left|\varepsilon_{x_H}^{(I,q)}(t)\right| \le Z^{(I,q)}(t) \quad (13)$$

where $Z^{(I,q)}(t)$ is defined in (9). ■

After the time instant of the first sensor fault occurrence in $\mathcal{S}^{(I,q)}$, denoted as $T_1^{(I,q)}$, the output of the group of sensors is described by (4). Hence, the nonlinear observer generates a 'faulty' estimation of the state vector of $\Sigma^{(I)}$, denoted as $\hat{x}_F^{(I,q)}(t)$, where $\hat{x}_F^{(I,q)}(t)$ is the solution of (5) for $t \ge T_1^{(I,q)}$. Thus, the j-th residual given in (6), for all $j \in \mathcal{J}^{(I,q)}$, is designed to be sensitive to the faults that occur in the group of sensors $\mathcal{S}^{(I,q)}$ only, i.e. $f^{(I,q)}$. Therefore, the residuals are characterized as structured, as well as the adaptive thresholds, whose computation is presented in the following Section.

B. Computation of adaptive thresholds

The utilization of adaptive thresholds is necessary for ensuring the robustness of the module $\mathcal{M}^{(I,q)}$ with respect to modeling uncertainties and noise. The adaptive threshold is a time-varying function that bounds the j-th residual under healthy conditions, $j \in \mathcal{J}^{(I,q)}$, which is described by

$$\varepsilon_{y_{jH}}^{(I,q)}(t) = C_j^{(I,q)} \varepsilon_{x_H}^{(I,q)}(t) + d_j^{(I,q)}(t). \qquad (14)$$

Introducing the solution of (8) in (14) and following the same procedure for computing $Z^{(I,q)}$ that bounds the state estimation error $\left|\varepsilon_{x_H}^{(I,q)}(t)\right|$, after choosing positive parameters $\alpha_j^{(I,q)}$, $\zeta_j^{(I,q)}$ such that $\left|C_j^{(I,q)} e^{A_L^{(I,q)} t}\right| \le \alpha_j^{(I,q)} e^{-\zeta_j^{(I,q)} t}$ and $\alpha_{d_j}^{(I,q)}$, $\zeta_{d_j}^{(I,q)}$ such that $\left|C_j^{(I,q)} e^{A_L^{(I,q)} t} L^{(I,q)}\right| \le \alpha_{d_j}^{(I,q)} e^{-\zeta_{d_j}^{(I,q)} t}$, we obtain

$$\begin{aligned} \bar{\varepsilon}_{y_j}^{(I,q)}(t) = & \alpha_j^{(I,q)} e^{-\zeta_j^{(I,q)} t} \bar{x}^{(I)} + \frac{\alpha_{d_j}^{(I,q)}}{\zeta_{d_j}^{(I,q)}} \bar{d}^{(I,q)} \left(1 - e^{-\zeta_{d_j}^{(I)} t}\right) \\ & + \int_0^t \alpha_j^{(I,q)} e^{-\zeta_j^{(I,q)}(t-\tau)} \Big(\bar{\eta}(\hat{x}^{(I,q)}(\tau), u^{(I)}(\tau), \tau) \\ & + \lambda_{h_I} \bar{z}^{(I)} + \Lambda_I Z^{(I,q)}(\tau)\Big) d\tau + \bar{d}_j^{(I,q)} \end{aligned} \qquad (15)$$

Under healthy conditions, the j-th adaptive threshold in (15) is computed using the healthy estimation $\hat{x}_H^{(I,q)}(t)$ and is denoted as $\bar{\varepsilon}_{y_{jH}}^{(I,q)}(t)$, which bounds the magnitude of the j-th residual under healthy conditions, i.e.

$$\left|\varepsilon_{y_{jH}}^{(I,q)}(t)\right| \le \bar{\varepsilon}_{y_{jH}}^{(I,q)}(t), \ j \in \mathcal{J}^{(I,q)} \qquad (16)$$

On the other hand, when sensor faults occur in the group of sensors $\mathcal{S}^{(I,q)}$, the observer $\mathcal{N}^{(I,q)}$ conveys a 'faulty' estimation $\hat{x}_F^{(I,q)}(t)$, which is used for computing the j-th threshold using (15). Consequently, the effects of the sensor faults $f^{(I,q)}$ may be reflected on the j-th adaptive threshold, $j \in \mathcal{J}^{(I,q)}$. It is important to note that the j-th adaptive threshold in (15), for all $j \in \mathcal{J}^{(I,q)}$, can be implemented by using linear filtering techniques.

C. Sensor Fault Detection Decision Logic

The primary goal of the module $\mathcal{M}^{(I,q)}$ is to infer about the presence of sensor faults in the group of sensors $\mathcal{S}^{(I,q)}$. This is realized based on the analytical redundancy relations (ARRs) [17], [19], which are formulated using the structured residuals and adaptive thresholds.

The j-th ARR, $j \in \mathcal{J}^{(I,q)}$, is defined as:

$$\mathcal{E}_j^{(I,q)}: \qquad \left|\varepsilon_{y_j}^{(I,q)}(t)\right| - \bar{\varepsilon}_{y_j}^{(I,q)}(t) \le 0. \qquad (17)$$

When inequality in (17) is true, then it is inferred that $\mathcal{E}_j^{(I,q)}$ is satisfied. The set of ARRs, based on which the module $\mathcal{M}^{(I,q)}$ obtains a decision, is defined as

$$\mathcal{E}^{(I,q)} = \bigcup_{j \in \mathcal{J}^{(I,q)}} \mathcal{E}_j^{(I,q)}. \qquad (18)$$

The set $\mathcal{E}^{(I,q)}$ is satisfied when $\mathcal{E}_j^{(I,q)}$ is satisfied for all $j \in \mathcal{J}^{(I,q)}$.

A key property of $\mathcal{E}^{(I,q)}$ for all I, q, is its robustness with respect to modeling uncertainties and noise; if no sensor fault occurs in $\mathcal{S}^{(I,q)}$ ($f^{(I,q)}(t) = 0$), $\varepsilon_{y_j}^{(I,q)}(t) = \varepsilon_{y_{jH}}^{(I,q)}(t)$ and $\bar{\varepsilon}_{y_j}^{(I,q)}(t) = \bar{\varepsilon}_{y_{jH}}^{(I,q)}(t)$, implying that (16) is valid for all $j \in \mathcal{J}^{(I,q)}$, or else $\mathcal{E}_j^{(I,q)}(t)$ is satisfied for all $j \in \mathcal{J}^{(I,q)}$. On the other hand, sensor faults $f^{(I,q)}(t)$ are detected according to the following theorem.

Theorem 4.2: If, at some finite time instant, $\mathcal{E}^{(I,q)}$ is not satisfied, i.e. for at least one $j \in \mathcal{J}^{(I,q)}$,

$$\left|\varepsilon_{y_j}^{(I,q)}(t)\right| - \bar{\varepsilon}_{y_j}^{(I,q)}(t) > 0, \qquad (19)$$

then the presence of faults in the group of sensors $\mathcal{S}^{(I,q)}$, $I \in \{1, \ldots, N\}$, is detected.

Proof: Theorem 4.2 can be proved by *reductio ad absurdum*; assume that no sensor fault has occurred. Then, $\varepsilon_{y_j}^{(I,q)}(t) = \varepsilon_{y_{jH}}^{(I,q)}(t)$ and $\bar{\varepsilon}_{y_j}^{(I,q)}(t) = \bar{\varepsilon}_{y_{jH}}^{(I,q)}(t)$, implying that (16) is valid. This contradicts the validity of (19). ■

The output of $\mathcal{M}^{(I,q)}$ is the decision on the presence of sensor faults in $\mathcal{S}^{(I,q)}$, represented by a boolean function, defined as

$$D^{(I,q)}(t) = \begin{cases} 0, & \text{if } D_j^{(I,q)}(t) = 0, \ \forall \ j \in \mathcal{J}^{(I,q)} \\ 1, & \text{otherwise} \end{cases} \qquad (20)$$

where $D_j^{(I,q)}(t) = 0$ if $t < T_j^{(I,q)}$, with $T_j^{(I,q)} = \min\left\{t : \left|\varepsilon_{y_j}^{(I,q)}(t)\right| - \bar{\varepsilon}_{y_j}^{(I,q)}(t) > 0\right\}$, and $D_j^{(I,q)}(t) = 1$ if $t \ge T_j^{(I,q)}$. If $\mathcal{E}_j^{(I,q)}$ is always satisfied, then $T_j^{(I,q)} \to \infty$. The time instant of fault detection is defined as $T_{FD}^{(I,q)} = \min\{T_j^{(I,q)}, j \in \mathcal{J}^{(I,q)}\}$.

V. Multiple Sensor Fault Isolation

The multiple sensor fault isolation (MSFI) decision logic implemented in the agent $\mathcal{M}^{(I)}$ is applied for isolating the combination of sensor faults that has occurred in $\mathcal{S}^{(I)}$, after the detection of the presence of sensor faults in at least one group of sensors.

The integration of decisions of the N_I modules is represented by the observed pattern of sensor faults, denoted as $D^{(I)}(t)$, which is defined as:

$$D^{(I)}(t) = \left[D^{(I,1)}(t), \ldots, D^{(I,N_I)}(t)\right]^\top \qquad (21)$$

where $D^{(I,q)}$, $q \in \{1, \ldots, N_I\}$, is the boolean decision function generated by the module $\mathcal{M}^{(I,q)}$ defined in (20).

Let us define $F^{(I)}$, $I \in \{1, \ldots, N\}$, as the combinatorial sensor fault signature matrix used in $\mathcal{M}^{(I)}$; the matrix $F^{(I)}$ is binary, consisting of N_I rows and Nc_I columns, where $Nc_I = 2^{m_I} - 1$ and m_I is the number of sensors in the local sensor set $\mathcal{S}^{(I)}$. The q-th row corresponds to the set of ARRs $\mathcal{E}^{(I,q)}$, $q \in \{1, \ldots, N_I\}$, while the i-th column corresponds to a combination of sensor faults that may occur in $\mathcal{S}^{(I)}$, denoted as $\mathcal{F}_{c_i}^{(I)}$, $i \in \{1, \ldots, Nc_I\}$. Each column of $F^{(I)}$ corresponds to the theoretical pattern of a sensor fault combination that may have affected $\mathcal{S}^{(I)}$, defined as

$$F_i^{(I)} = \left[F_{1i}^{(I)}, \ldots, F_{N_I i}^{(I)}\right]^\top, \qquad (22)$$

where $F_{qi}^{(I)} = 1$, $q \in \{1, \ldots, N_I\}$, $i \in \{1, \ldots, Nc_I\}$, if at least one sensor fault that belongs to the combination $\mathcal{F}_{c_i}^{(I)}$ is involved in $\mathcal{E}^{(I,q)}$, and $F_{qi}^{(I)} = 0$ otherwise.

The goal of multiple sensor fault isolation procedure is to compare the observed pattern of sensor faults, $D^{(I)}(t)$ to each of the theoretical patterns of sensor fault combinations, $F_i^{(I)}$. An observed sensor fault pattern $D^{(I)}(t)$ is said to be consistent with the i-th theoretical sensor fault pattern $F_i^{(I)}$ if $D^{(I,q)}(t) = F_{qi}^{(I)}$, for all $q \in \{1, \dots, N_I\}$ (if $D^{(I)}(t) = \mathbf{0_{N_I}}$, no comparison is realized). The result of checking the consistency between the observed and theoretical sensor fault patterns is the determination of the *diagnosis set* defined as:

$$\mathcal{D}_s^{(I)}(t) = \left\{ \mathcal{F}_{c_i}^{(I)} : i \in \mathcal{I}_{\mathcal{D}}^{(I)} \right\} \tag{23}$$

where $\mathcal{I}_{\mathcal{D}}^{(I)} = \left\{ i : F_i^{(I)} = D^{(I)}(t), i \in \{1, \dots, Nc_I\} \right\}$. However, there may be a time instant at which the observed pattern does not match any of the theoretical patterns. This can happen, when a sensor fault $f_j^{(I)}$, $j \in \mathcal{J}^{(I,q)}$ of the combination $\mathcal{F}_{c_i}^{(I)}$, $i \in \{1, \dots, Nc_I\}$, which is involved in more than one set of ARRs, provokes the violation of these sets of ARRs in different time instances, because some ARRs may be more sensitive to $f_j^{(I)} \in \mathcal{F}_{c_i}^{(I)}$ than other ARRs. In this case, the diagnosis set is determined based on the support of the violated $\mathcal{E}^{(I,q)}$ [19]. The support of $\mathcal{E}^{(I,q)}$, denoted as $Supp(\mathcal{E}^{(I,q^*)})$, is a set, which includes the combinations of sensor faults $\mathcal{F}_{c_i}^{(I)}$ with 1 in the row corresponding this $\mathcal{E}^{(I,q)}$, i.e. $F_{qi}^{(I)} = 1$. In this case, the diagnosis set is defined as

$$\mathcal{D}_s^{(I)}(t) = \bigcap_{q^* \in \mathcal{Q}(t)} Supp(\mathcal{E}^{(I,q^*)}). \tag{24}$$

where $\mathcal{Q}(t) = \{q : D^{(I,q)}(t) = 1,\ q \in \{1, \dots, N_I\}\}$.

Based on the diagnosis set $\mathcal{D}_s^{(I)}(t)$, we can infer that: i) at least one of the sensor fault combinations in $\mathcal{D}_s^{(I)}(t)$ has occurred, ii) the sensor faults included in $\bigcap_{i \in \mathcal{I}_{\mathcal{D}}^{(I)}} \mathcal{F}_{c_i}^{(I)}$ are guaranteed to have occurred and iii) the occurrence of the sensor fault combination $\mathcal{F}_{c_i}^{(I)} \notin \bigcap_{q \in \mathcal{Q}(t)} Supp(\mathcal{E}^{(I,q)})$ is excluded.

VI. Simulation Example

In this section, we illustrate the application of the multiple sensor fault detection and isolation methodology to an automated highway system (AHS); i.e., a platoon of vehicles that are driven automatically using on-board controllers [23]. The goal is to detect and isolate multiple faults that affect the sensors of each vehicle .

The dynamics of the vehicle-following system for the I-th vehicle, $I = 1, 2, 3$ ($I = 1$ stands for the leading vehicle) can be described by :

$$\dot{\psi}^{(I)}(t) = v^{(I)}(t) - v^{(I-1)}(t) + \eta_\psi(t), \tag{25}$$

$$\dot{v}^{(I)}(t) = \frac{1}{m}\left(-\phi - \delta_A \cdot \left(v^{(I)}(t)\right)^2 + w^{(I)}(t) \right), \tag{26}$$

$$\dot{w}^{(I)}(t) = \frac{1}{\tau + \Delta\tau}\left(-w^{(I)}(t) + u^{(I)}(t) \right), \tag{27}$$

where $\psi^{(I)}$ is the intervehicle spacing between the I and $I-1$ vehicle, $v^{(I)}$ is the velocity of the I-th vehicle, $w^{(I)}$ is the driving/braking force applied to the longitudinal dynamics of the I-th vehicle, $u^{(I)}$ is the control input of the I-th vehicle, the function η_ψ is a disturbance signal defined as $\eta_\psi(t) = \sigma \sin(t)$ for all $I = 1, 2, 3$, with $|\sigma| \le 0.5$, and $\Delta\tau$ corresponds to inaccuracy in the engine/brake time constant with $|\Delta\tau| \le 5\%\tau$. Moreover, it is assumed that the reference velocity of the leading car is $v_r^{(1)}(t) = 40 + 5\sin(t)$, satisfying $\lim_{t\to\infty} \left| v^{(1)}(t) - v_r^{(1)}(t) \right| \le \bar{v}$ with $\bar{v} = 12$. The Lipschitz constants satisfy $\lambda_{\gamma_I} = 0.0462$ and $\lambda_{h_I} = 1$. The model parameters, including the mass of the vehicle m, the constant frictional force ϕ, the aerodynamic drag δ_A and the engine/brake time constant τ, are the same for each vehicle and are chosen as in [23], [24]. The dynamic model of the vehicle-following system (25)-(27) can be re-written as in (1) with $x^{(I)} = \left[\psi^{(I)}, v^{(I)}, w^{(I)}\right]^\top$ and $z^{(I)} = v^{(I-1)}$.

In each vehicle there are three sensors installed, which constitute the local sensor set $\mathcal{S}^{(I)} = \left\{ \mathcal{S}^{(I)}\{1\}, \mathcal{S}^{(I)}\{2\}, \mathcal{S}^{(I)}\{3\} \right\}$, characterized by (2), with $C^{(I)} = [1\ 0.4\ 0; 0\ 1\ 0; 0\ 0\ 1]$. The noise of each sensor satisfies $|d_j^{(I)}(t)| \le \bar{d}_j^{(I)}$, where $\bar{d}_q^{(I)} = 1\% Y_q^{(I)}$, and $Y_1^{(I)}$, $Y_2^{(I)}$, $Y_3^{(I)}$ are the amplitudes of the outputs of the sensors $y_1^{(I)}, y_2^{(I)}, y_3^{(I)}$, respectively, under healthy conditions. Three decentralized backstepping controllers are designed such that the leading car should follow the reference velocity $v_r^{(1)}(t)$, while the following vehicles are designed to keep the intervehicle spacing distance constant; i.e., $\psi^{(I)} = -10$, $I = 2, 3$.

For each of the three vehicles, we design a LSFD agent $\mathcal{M}^{(I)}$ which is responsible for detecting and isolating faults in the sensor set $\mathcal{S}^{(I)}$. Each agent consists of a bank of three modules such that the module $\mathcal{M}^{(I,q)}$ monitors the sensor $\mathcal{S}^{(I,q)} = \mathcal{S}^{(I)}\{q\}$, $q \in \{1, 2, 3\}$, where $\mathcal{S}^{(I)}\{q\}$ is characterized by $y_q^{(I)} = C_q^{(I)} x^{(I)} + d_q^{(I)} + f_q^{(I)}$. We design three stable observers such that the observer $\mathcal{N}^{(I,q)}$, $q \in \{1, 2, 3\}$, uses the measurements $y_q^{(I)}$ and can estimate them. The decision logic of the module $\mathcal{M}^{(I,q)}$ is based on checking whether $\mathcal{E}^{(I,q)} = \mathcal{E}_q^{(I,q)}$ is satisfied, where $\mathcal{E}_q^{(I,q)}$ is formulated using the residual $\varepsilon_{y_q}^{(I,q)} = y_q^{(I)} - C_q^{(I)} \hat{x}^{(I,q)}$ and the corresponding adaptive threshold. The multiple sensor fault isolation decision logic implemented in the agent $\mathcal{M}^{(I)}$, $I = 1, 2, 3$ is based on the multiple sensor fault signature matrix presented in Table I, where the j-th rows corresponds to $\mathcal{E}^{(I,j)}$, $j = 1, 2, 3$ and there are seven columns corresponding to the following sensor fault combinations: $\mathcal{F}_{c_1}^{(I)} = \left\{ f_1^{(I)} \right\}$, $\mathcal{F}_{c_2}^{(I)} = \left\{ f_2^{(I)} \right\}$, $\mathcal{F}_{c_3}^{(I)} = \left\{ f_3^{(I)} \right\}$, $\mathcal{F}_{c_4}^{(I)} = \left\{ f_1^{(I)}, f_2^{(I)} \right\}$, $\mathcal{F}_{c_5}^{(I)} = \left\{ f_1^{(I)}, f_3^{(I)} \right\}$, $\mathcal{F}_{c_6}^{(I)} = \left\{ f_2^{(I)}, f_3^{(I)} \right\}$ and $\mathcal{F}_{c_7}^{(I)} = \left\{ f_1^{(I)}, f_2^{(I)}, f_3^{(I)} \right\}$. As observed by this matrix, there are seven distinct theoretical patterns of sensor fault combinations, implying that all the sensor fault combinations that may occur in the I-th vehicle are isolable for all $I = 1, 2, 3$.

The simulations have been conducted considering the occurrence of multiple, abrupt sensor faults in each vehicle, such that 1) $f_2^{(1)} = 10\% Y_2^{(1)}$, $T_{f_2}^{(1)} = 150$ sec 2) $f_3^{(1)} = 15\% Y_2^{(1)}$, $T_{f_3}^{(1)} = 160$ sec, 3) $f_1^{(2)} = 25\% Y_1^{(2)}$, $T_{f_1}^{(2)} = 170$

	$\mathcal{F}_{c_1}^{(I)}$	$\mathcal{F}_{c_2}^{(I)}$	$\mathcal{F}_{c_3}^{(I)}$	$\mathcal{F}_{c_4}^{(I)}$	$\mathcal{F}_{c_5}^{(I)}$	$\mathcal{F}_{c_6}^{(I)}$	$\mathcal{F}_{c_7}^{(I)}$
$\mathcal{E}^{(I,1)}$	1	0	0	1	1	0	1
$\mathcal{E}^{(I,2)}$	0	1	0	1	0	1	1
$\mathcal{E}^{(I,3)}$	0	0	1	0	1	1	1

TABLE I: Multiple sensor fault signature matrix implemented in the I-th LSFD agent, $I = 1, 2, 3$.

sec, and 4) $f_3^{(2)} = 15\% Y_3^{(2)}$, $T_{f_3}^{(2)} = 180$ sec. Figure 1 presents the time evolution of decision functions $D^{(I,q)}$ $q, I = 1, 2, 3$. Particularly, the I-th row of subfigures depicts the observed pattern $D^{(I)}(t)$, which is compared at every time instant to each of the seven theoretical patterns, i.e. columns of Table I. It can be observed that all sensor faults have been isolated, according to the following diagnosis sets: $\mathcal{D}_s^{(1)}(t) = \left\{\mathcal{F}_{c_2}^{(1)}\right\}$, for $150 \leq t < 160$, $\mathcal{D}_s^{(1)}(t) = \left\{\mathcal{F}_{c_6}^{(1)}\right\}$, for $t \geq 160$, $\mathcal{D}_s^{(2)}(t) = \left\{\mathcal{F}_{c_1}^{(2)}\right\}$, for $160 \leq t < 180$, $\mathcal{D}_s^{(2)}(t) = \left\{\mathcal{F}_{c_5}^{(2)}\right\}$, for $t \geq 180$.

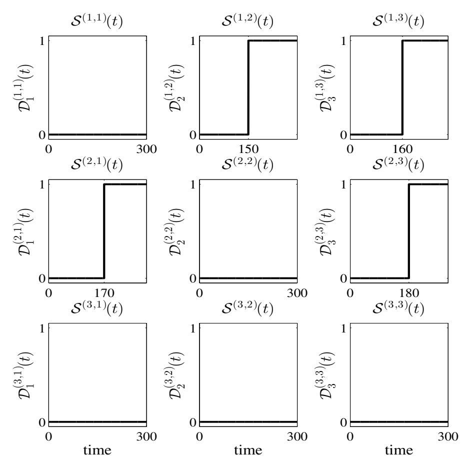

Fig. 1: Isolation of multiple sensor faults that occur in the three vehicles

VII. Conclusions

In this paper, a model-based architecture for detecting and isolating multiple sensor faults in large-scale interconnected, nonlinear systems is presented. The proposed architecture is based on the deployment of decentralized local sensor fault diagnosis (LSFD) agents. Each LSFD agent is dedicated to each of the interconnected subsystems, aiming at diagnosing sensor faults in the local sensor set. This is realized in two stages. In the first stage, a bank of modules is used for detecting faults in smaller groups of sensors that belong the local sensor set, with each module designed to monitor a single sensor group. In the second stage, the decisions of modules is aggregated and processed using a reasoning-based decision logic and a multiple sensor fault signature matrix. An automated highway system was utilized for illustrating the application of the proposed architecture.

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