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A distributed virtual sensor scheme for marine fuel engines ⋆

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Abstract: This paper proposes a virtual sensor scheme designed to compensate for sensor fault effects in marine fuel engines. The proposed scheme design follows a distributed approach, where the marine fuel engine is decomposed in several subsystems. Then, for each subsystem we design a monitoring agent that can actively compensate for the effects of sensor faults occurring in the specific subsystem. This is realized using virtual sensors that can estimate the sensor fault in order to reconstruct the faulty measurements. Due to the Differential-Algebraic mathematical description of marine fuel engine dynamics, we design three types of virtual sensors; using adaptive observers, Set Inversion via Interval Analysis (SIVIA) and static models. Simulation results are used to illustrate the efficiency of the method.

Keywords: Fault accommodation, fault identification, sensor faults, Differential–algebraic equations (DAE's), nonlinear systems, Marine system modelling, interconnected systems

1. INTRODUCTION

Ensuring safety is a prerequisite for modern marine vessels and a basic pillar for the development of future autonomous ships [de Vos et al. (2021)]. In order to promote safety on-board marine vessels, better monitoring of the vessel's vital systems and sensors such as the propulsion system, that may include more than one marine fuel engine.

Modern vessels are equipped with thousands of sensors dispersed in the various on-board machinery and used for condition monitoring purposes. Despite their importance, little attention has been given to assessing sensor health, and sensor faults have been mostly overlooked in literature. However, sensor measurements should be reliable for effective control and maintenance of marine vessels. The recovery from sensor faults can be accomplished using either physical [Wu et al. (2006)] or analytical redundancy [Darvishi et al. (2021); Blanke et al. (1998)]. In the first case, multiple hardware sensors of the same type are used to check the sanity of the measurements and restore operation. The latter case, on the other hand, involves the creation of virtual sensors to perform a similar task using model information.

In the area of sensor fault accommodation of marine fuel engines there has been some activity both considering model-based and model-free methods. Blanke et al. (1998) propose accommodation for faults in the shaft speed sensor of a marine diesel propulsion system using software-based sensors. Both static models and nonlinear observers are considered in their approach and the methodology manages to render a minimal overshoot during switching. In [Ou et al. (2022)], the authors present a model-based identification method for the combustion system of marine fuel engines. More specifically, thermodynamic models are used to detect abnormal behaviour in measurement data and reconstruct the data. However, in both papers simple models of the marine fuel engine and only single faults are considered. Concerning model-free methods, in [Campa et al. (2008)] a sensor validation scheme is proposed for heavy-duty diesel engines. In addition, a hybrid scheme composed of Adaptive Linear (ADALINE) Neural Networks for linear engine operating conditions as well as Minimal Resource Allocating Networks (MRAN) for nonlinear engine conditions is proposed for approximating faulty sensor measurements. Darvishi et al. (2021) propose a machine-learning-based framework for sensor validation based on a multilayer perceptron neural network architecture for marine vessels. Both ADALINE and MRAN require a high number of neurons to calculate the output due to the high system nonlinearity and the detectability of sensor faults depends on the accuracy of the used training sets. Moreover, the generalization ability of the produced results is low.

This paper provides a methodology for the identification of faults affecting multiple sensors of marine fuel engines and for the reconstruction of faulty measurements to restore normal operation (see Section 4). The identification of sensor faults relies on the use of a mixed scheme combining three types of virtual sensors that perform state and fault estimation and whose design is based on a Mean Value First Principle (MVFP) model which can describe the actual engine more accurately (see Section 3). This model incorporates both differential and algebraic

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equations (DAE) according to the general mathematical formulation shown in Section 2. As for the reconstruction of sensor faults, the estimated faults are subtracted from the faulty sensor measurements, based on the results of the identification step.

From the application point of view, the main contribution of this paper is the proposed virtual sensor scheme for marine fuel engines. This serves as a continuation of previous work [Kougiatsos et al. (2022)] which focused on providing a suitable sensor fault diagnosis methodology for these type of engines using a mixed Differential-Algebraic diagnosis scheme. Moreover, the MVFP engine model provides better generalization ability of the results for different engines, since it can be reconfigured in its parameters and can also be expanded to host more subsystems and sensors. Compared to the state-of-art in virtual sensor design that considers dynamical systems described by differential equations [Zhang et al. (2008); Blanke et al. (2016); Papadopoulos (2020)], we consider a differential-algebraic description for the marine fuel engine system. More specifically, for parts of the system described by differential equations, nonlinear observers are suggested, for parts described by explicit algebraic equations we use static nonlinear estimators and for parts described by implicit algebraic equations, estimators based on set inversion via interval analysis (SIVIA) are used.

2. PROBLEM FORMULATION

Marine fuel engines are complex systems incorporating components characterised by heterogeneous dynamics and inherent interconnections. In Fig. 1 a representation of a marine fuel engine is shown, where the different parts are grouped in four distinct subsystems and a total of ten sensors are deployed for condition monitoring.

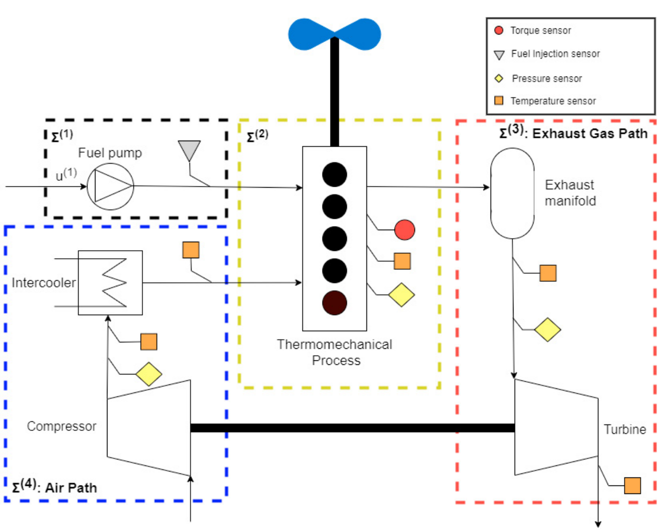

Fig. 1. Schematic representation of a typical marine fuel engine

Given the heterogeneous dynamics and interconnections of the subsystems in marine fuel engines, the proposed sensor fault accommodation method is developed considering a class of N nonlinear DAE-based interconnected systems $\Sigma^{(I)}, I = 1, \cdots, N$ described by [Vemuri et al. (2001)]:

$$\Sigma^{(I)} : \begin{cases} \dot{x}^{(I)}(t) = A^{(I)}x^{(I)}(t) + \gamma^{(I)}(x^{(I)}(t), z^{(I)}(t), u^{(I)}(t)) + \\ h^{(I)}(x^{(I)}(t), z^{(I)}(t), \chi^{(I)}(t), u^{(I)}(t)) + \eta_x^{(I)}(t), & \text{(1a)} \\ 0 = \xi^{(I)}(x^{(I)}(t), z^{(I)}(t), \chi^{(I)}(t), u^{(I)}(t)) + \eta_z^{(I)}(t) & \text{(1b)} \end{cases}$$

where $x^{(I)} \in \mathbb{R}^{n_I - r_I}$ is the state variable vector, $z^{(I)} \in \mathbb{R}^{r_I}$ is the algebraic variable vector, $\chi^{(I)} \in \mathbb{R}^{k_I}$ are the interconnection variables from the neighbouring subsystems, $u^{(I)} \in \mathbb{R}^{l_I}$ is the control input vector, $\gamma^{(I)} : \mathbb{R}^{n_I - r_I} \times \mathbb{R}^{l_I} \mapsto \mathbb{R}^{n_I - r_I}$ represents the known nonlinear system dynamics, $h^{(I)} : \mathbb{R}^{n_I - r_I} \times \mathbb{R}^{r_I} \times \mathbb{R}^{k_I} \times \mathbb{R}^{l_I} \mapsto \mathbb{R}^{n_I - r_I}$ represents the known interconnection dynamics with the neighbouring subsystems, $\eta_x^{(I)} \in \mathbb{R}^{n_I - r_I}, \eta_z^{(I)} \in \mathbb{R}^{r_I}$ represent the system disturbances, $\xi^{(I)} : \mathbb{R}^{n_I} \times \mathbb{R}^{k_I} \times \mathbb{R}^{l_I} \mapsto \mathbb{R}^{n_I - r_I}$ is a smooth vector field.The term $A^{(I)}x^{(I)}$ represents the linear part of the system's $\Sigma^{(I)}$ dynamics, where $A^{(I)} \in \mathbb{R}^{(n_I - r_I)\times(n_I - r_I)}$ is assumed known.

Each system incorporates a set of sensors $\mathcal{S}^{(I)} = \bigcup_{j=1}^{n_I} \mathcal{S}^{(I)}\{j\}$ described as:

$$\mathcal{S}^{(I)} : \begin{cases} y_x^{(I)}(t) = x^{(I)}(t) + d_x^{(I)}(t) + f_x^{(I)}(t) \\ y_z^{(I)}(t) = z^{(I)}(t) + d_z^{(I)}(t) + f_z^{(I)}(t) \end{cases} \quad (2)$$

where $y_x^{(I)} \in \mathbb{R}^{n_I - r_I}$ denotes the sensor values corresponding to state variables, $y_z^{(I)} \in \mathbb{R}^{r_I}$ denotes the sensor values corresponding to algebraic variables, $d_x^{(I)} \in \mathbb{R}^{n_I - r_I}$, $d_z^{(I)} \in \mathbb{R}^{r_I}$ are the measurement noise vectors and $f_x^{(I)} \in \mathbb{R}^{n_I - r_I}$, $f_z^{(I)} \in \mathbb{R}^{r_I}$ are sensor fault vectors. Each fault vector is given by $f^{(I)}(t) = [f_x^{(I)}(t)\ f_z^{(I)}(t)]^\top = [f_1^{(I)}(t), \cdots, f_{n_I}^{(I)}(t)]^\top$, where $f_j^{(I)}(t), j \in \{1, \cdots, n_I\}$ denotes the change in the output due to a fault in the j-th sensor, occurring at time $T_{f_j}^{(I)}$.

The goal of this paper is to design a distributed virtual sensor scheme to reconstruct the faulty measurements for ensuring reliable condition monitoring and control of the engine operation, avoiding the propagation of sensor fault effects.

3. FUEL ENGINE STATE-SPACE MODELLING

In order to describe the operation of the fuel engine, the physical MVFP model described in [Geertsma et al. (2017)] is used. Based on the system decomposition shown in Fig. 1, we consider four nonlinear interconnected subsystems described by nonlinear DAE expressed by (1), (2). For simplicity purposes, the time dependence may hereby be omitted.

3.1 Fuel Pump ($\Sigma^{(1)}$)

Subsystem 1 is expressed as:

$$\Sigma^{(1)} : \dot{x}^{(1)} = -\frac{1}{\tau_X}x^{(1)} + \frac{x_{nom}^{(1)}}{\tau_X}u^{(1)} \quad (3)$$

where $x^{(1)}(t) \in \mathbb{R}$ is the amount of fuel injected per cylinder per engine cycle in kg, $x_{nom}^{(1)} \in \mathbb{R}$ signifies the same quantity under nominal conditions , $u(t) \in \mathbb{R}$ is the fuel injection setting in % and n_{fe}^{nom}, $\tau_X = \frac{1}{4n_{fe}^{nom}}$, SFC^{nom}, P_{fe}^{nom}, i_e, k_e are defined in [Geertsma et al. (2017)]. The output of the fuel injection sensor $y^{(1)} \in \mathbb{R}$ is described by:

$$\mathcal{S}^{(1)} : y^{(1)} = x^{(1)}(t) + d^{(1)} + f^{(1)} \tag{4}$$

3.2 Thermomechanical process ($\Sigma^{(2)}$)

This subsystem has 3 algebraic variables, namely the pressure ($z_1^{(2)}$) in Pa and the temperature ($z_2^{(2)}$) in K inside the engine's cylinders and the engine's shaft torque ($z_3^{(2)}$) in Nm. The mathematical representation of the system is:

$$\Sigma^{(2)} : 0 = \begin{bmatrix} z_1^{(2)} - \xi_{z1}^{(2)}(x^{(1)}, z_3^{(2)}, x^{(4)}, z_1^{(4)}) \\ z_2^{(2)} - \xi_{z2}^{(2)}(x^{(1)}, z_3^{(2)}, x^{(4)}, z_1^{(4)}) \\ z_3^{(2)} - \xi_{z3}^{(2)}(x^{(1)}, z_3^{(2)}, x^{(4)}, z_1^{(4)}) \end{bmatrix} \tag{5}$$

where the functions $\xi_{z1}^{(2)}, \xi_{z2}^{(2)}, \xi_{z3}^{(2)} \in \mathbb{R}$ can be modelled using the Seilinger thermodynamic cycle as described in detail in [Kougiatsos et al. (2022)].

The output values of the pressure, temperature and torque sensors $y^{(2)} \in \mathbb{R}^3$ are described by:

$$\mathcal{S}^{(2)} : y^{(2)} = z^{(2)} + d^{(2)} + f^{(2)} \tag{6}$$

3.3 Exhaust Gas Path ($\Sigma^{(3)}$)

This subsystem has 1 state-variable, the exhaust receiver pressure ($x^{(3)}$) in Pa and 2 algebraic variables, the temperature before ($z_1^{(3)}$) and after ($z_2^{(3)}$) the turbine in K. This subsystem is represented as follows in state-space:

$$\Sigma^{(3)} : \begin{cases} \dot{x}^{(3)} = -\frac{1}{\tau_{p_d}} x^{(3)} + h^{(3)}(x^{(3)}, z^{(3)}, \chi^{(3)}) \\ 0 = \quad \xi^{(3)}(x^{(3)}, z^{(3)}, \chi^{(3)}) \end{cases} \tag{7}$$

where $\chi^{(3)} = [x^{(1)}, z^{(2)}, x^{(4)}, z^{(4)}]^\top$ are the interconnection variables. The interconnection dynamics denoted by $h^{(3)}$ and $\xi^{(3)}$ have already been defined in [Kougiatsos et al. (2022)]. The related set of sensors is expressed as:

$$\mathcal{S}^{(3)} : y^{(3)} = \left[\, x^{(3)} \; z^{(3)} \,\right]^\top + d^{(3)} + f^{(3)} \tag{8}$$

3.4 Air Path ($\Sigma^{(4)}$)

This subsystem has 1 state-variable, the charge air pressure after the compressor ($x^{(4)}$) in Pa and 2 algebraic variables, the temperatures before ($z_1^{(4)}$) and after ($z_2^{(4)}$) the intercooler in K. This subsystem is represented as follows in state-space:

$$\Sigma^{(4)} : \begin{cases} \dot{x}^{(4)} = -\frac{1}{\tau_{TC}} x^{(4)} + h^{(4)}(x^{(4)}, z^{(4)}, \chi^{(4)}) \\ 0 = \quad \xi^{(4)}(x^{(4)}, z^{(4)}, \chi^{(4)}) \end{cases} \tag{9}$$

where $\chi^{(4)} = [x^{(1)}, z^{(2)}, x^{(3)}, z^{(3)}]^\top$ are the interconnection variables. The interconnection dynamics denoted by $h^{(4)}$ and $\xi^{(4)}$ have already been defined in [Kougiatsos et al. (2022)]. The sensor set of this system is given by:

$$\mathcal{S}^{(4)} : y^{(4)} = \left[\, x^{(4)} \; z^{(4)} \,\right]^\top + d^{(4)} + f^{(4)} \tag{10}$$

4. DISTRIBUTED VIRTUAL SENSOR SCHEME

The proposed virtual sensor scheme is activated after the detection and isolation of sensor faults, using the method developed in [Kougiatsos et al. (2022)]. The details of the method are omitted for brevity. As can be seen from Figure 2 for each one of the fuel engine's subsystems $\Sigma^{(I)}$, $I = 1, \cdots, N$ (N=4), a monitoring agent $\mathcal{M}^{(I)}$ has been designed. Each agent consists of N_I modules $\mathcal{M}^{(I,q)}$, $q = 1, \cdots, N_I$ ($N_1 = 1,\ N_2 = N_3 = N_4 = 3$), that monitor specific sensor subsets $\mathcal{S}^{(I,q)} \subseteq \mathcal{S}^{(I)}$ in the designated subsystem. Every $\mathcal{S}^{(I,q)}$ contains sensors measuring either state or algebraic variables. The 10 sensors of

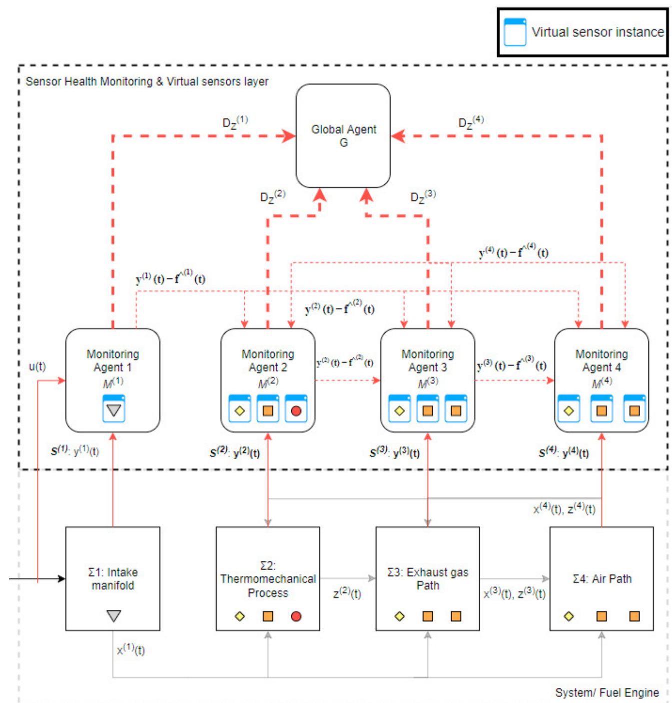

Fig. 2. Distributed Sensor Fault Diagnosis scheme with the addition of virtual sensors

the system are divided in the following sensor sets: $\mathcal{S}^{(1,1)} = \{\mathcal{S}^{(1)}\{1\}\}, \mathcal{S}^{(2,1)} = \{\mathcal{S}^{(2)}\{1\}\}, \mathcal{S}^{(2,2)} = \{\mathcal{S}^{(2)}\{2\}\}, \mathcal{S}^{(2,3)} = \{\mathcal{S}^{(2)}\{2\}, \mathcal{S}^{(2)}\{3\}\}$, $\mathcal{S}^{(3,1)} = \{\mathcal{S}^{(3)}\{1\}, \mathcal{S}^{(3)}\{2\}\}$, $\mathcal{S}^{(3,2)} = \{\mathcal{S}^{(3)}\{1\}, \mathcal{S}^{(3)}\{2\}\}$, $\mathcal{S}^{(3,3)} = \{\mathcal{S}^{(3)}\{1\}, \mathcal{S}^{(3)}\{2\}, \mathcal{S}^{(3)}\{3\}\}$, $\mathcal{S}^{(4,1)} = \{\mathcal{S}^{(4)}\{1\}, \mathcal{S}^{(4)}\{2\}\}$, $\mathcal{S}^{(4,2)} = \{\mathcal{S}^{(4)}\{2\}\}$, $\mathcal{S}^{(4,3)} = \{\mathcal{S}^{(4)}\{2\}, \mathcal{S}^{(4)}\{3\}\}$. Each of the modules $\mathcal{M}^{(I,q)}$ is then designed to use the information from the respective sensors in $\mathcal{S}^{(I,q)}$. From this point onwards, the following notations will be used: $y_x^{(1,1)} = y^{(1)}$, $y_z^{(2,1)} = y_1^{(2)}$, $y_z^{(2,2)} = y_2^{(2)}$, $y_z^{(2,3)} = y_3^{(2)}$, $y_x^{(3,1)} = y_1^{(3)}$, $y_z^{(3,2)} = y_2^{(3)}$, $y_z^{(3,3)} = y_3^{(3)}$, $y_x^{(4,1)} = y_1^{(4)}$, $y_z^{(4,2)} = y_2^{(4)}$, $y_z^{(4,3)} = y_3^{(4)}$. Notably, dynamic virtual sensors are used for the modules $\mathcal{M}^{(1,1)}$, $\mathcal{M}^{(3,1)}$, $\mathcal{M}^{(4,1)}$, static virtual sensors are used for the modules $\mathcal{M}^{(2,1)}$, $\mathcal{M}^{(2,2)}$, $\mathcal{M}^{(3,2)}$, $\mathcal{M}^{(3,3)}$, $\mathcal{M}^{(4,2)}$, $\mathcal{M}^{(4,3)}$ and a SIVIA-based virtual sensor is used for the module $\mathcal{M}^{(2,3)}$. The proposed virtual sensor scheme aims to guarantee proper condition monitoring of the fuel engine system and to maintain the performance of the engine control system.

To this end, and as can be seen in Figure 2, reconstructed measurements can be used instead of the measurements provided by the sensors, defined as follows:

$$\begin{cases} y_{xH}^{(I,q)} = y_x^{(I,q)} - \hat{f}_x^{(I,q)} \\ y_{zH}^{(I,q)} = y_z^{(I,q)} - \hat{f}_z^{(I,q)} \end{cases} \tag{11}$$

where $\hat{f}_x^{(I,q)}$, $\hat{f}_z^{(I,q)}$ are the estimations of the sensors faults using the identification methodology described in the next Subsection ??. If no sensor faults are diagnosed, then $y_{xH}^{(I,q)} = y_x^{(I,q)}$ and $y_{zH}^{(I,q)} = y_z^{(I,q)}$.

We assume that the system disturbance and the measurement noise of each sensor are unknown but uniformly bounded, meaning: $\left|\eta_{xj}^{(I)}\right| \leqslant \overline{\eta}_{xj}^{(I)}$, $\left|\eta_{zj}^{(I)}\right| \leqslant \overline{\eta}_{zj}^{(I)}$, $\left|d_j^{(I)}\right| \leqslant \overline{d}_j^{(I)}, \forall j \in 1, \cdots, n_I$ where $\overline{\eta}_{xj}^{(I)}, \overline{\eta}_{zj}^{(I)}, \overline{d}_j^{(I)}$ are known.

4.1 Distributed dynamic virtual sensors

Considering (1a), the sensor fault can be estimated using a distributed adaptive estimator scheme described as:

$$\begin{cases} \dot{\hat{x}}^{(I,q)} = A^{(I)}\hat{x}^{(I,q)} + \gamma^{(I)}(\hat{x}^{(I,q)}, y_{zH}^{(I)}, u^{(I)}) + \\ h^{(I)}(\hat{x}^{(I,q)}, y_{zH}^{(I)}, y_{\chi H}^{(I,q)}, u^{(I)}) + L^{(I,q)}(y_x^{(I,q)} - \hat{y}_x^{(I,q)}) + \\ \Omega^{(I,q)}\dot{\hat{f}}_x^{(I,q)} & (12a) \\ \dot{\Omega}^{(I,q)} = A_L^{(I,q)}\Omega^{(I,q)} - L^{(I,q)} & (12b) \\ \hat{y}_x^{(I,q)}(t) = \hat{x}^{(I,q)} + \hat{f}_x^{(I,q)} & (12c) \\ \dot{\hat{f}}_x^{(I,q)} = \Gamma^{(I,q)}(\Omega^{(I,q)} + 1)\mathcal{D}[\epsilon_{y_x}{}^{(I,q)}] & (12d) \end{cases}$$

where $L^{(I,q)}$ is the estimator gain such that $A_L^{(I,q)} \triangleq A^{(I)} - L^{(I,q)}$ is Hurwitz, $\Gamma^{(I,q)}$ is the learning rate of the adaptive law in (12d) and $\Omega^{(I,q)}$ is a filtering term to ensure the stability of the adaptive scheme. Finally, $\mathcal{D}[\cdot]$ is the dead-zone operator, used to activate the sensor fault identification, given as:

$$\mathcal{D}[\epsilon_{y_x}{}^{(I,q)}] = \begin{cases} 0, & if\ D^{(I,q)}(t) = 0 \\ \epsilon_{y_x}{}^{(I,q)}, & if\ D^{(I,q)}(t) = 1 \end{cases} \quad (13)$$

where $\epsilon_{y_x}{}^{(I,q)} \triangleq y_x^{(I,q)} - \hat{x}^{(I,q)} - \hat{f}_x^{(I,q)}$ and $D^{(I,q)}$ denotes the binary decision of the monitoring module $\mathcal{M}^{(I,q)}$ on the occurrence of sensor faults as part of the diagnosis process.

4.2 Distributed algebraic virtual sensors

Considering algebraic equations of the form (1b) we design two types of algebraic virtual sensors.

Static virtual sensors: When (1b) is written in an explicit form $z^{(I)}(t) = \xi_z^{(I)}(x^{(I)}(t), \chi^{(I)}(t), u^{(I)}(t))$, the following estimator can be used:

$$\begin{cases} \hat{z}^{(I,q)} = \hat{\xi}_z^{(I)}(y_{xH}^{(I,q)}, y_{\chi H}^{(I,q)}, u^{(I)}) & (14a) \\ \hat{f}_z^{(I,q)} = (y_z^{(I,q)} - \hat{z}^{(I,q)})D^{(I,q)} & (14b) \end{cases}$$

SIVIA-based virtual sensors: For all other cases (implicit algebraic equations), the use of SIVIA [Jaulin and Walter (1993)] is proposed. The rationale behind SIVIA is the identification of sets of nonlinear functions with the guaranteed property of convergence.

Hereby, the notation $[\cdot]$ will be used to denote an interval. Using (1b), the following approximator can be constructed:

$$0 = \xi^{(I,q)}(x^{(I,q)}, \hat{z}^{(I,q)}, \chi^{(I,q)}, u^{(I)}) \quad (15)$$

From (2), the following intervals are known: $[x^{(I,q)}] = y_x^{(I,q)} - \hat{f}_x^{(I,q)} + [d_x^{(I,q)}]$ $([x_j^{(I,q)}] = [y_{x_j}^{(I,q)} - \hat{f}_x^{(I,q)} - \bar{d}_{x_j}^{(I,q)}, y_{x_j}^{(I,q)} - \hat{f}_x^{(I,q)} + \bar{d}_{x_j}^{(I,q)}] = \hat{x}_j^{(I,q)} + [d_{x_j}^{(I,q)}],\ j = 1, \cdots, n_I - r_I)$, $[\chi^{(I,q)}] = y_\chi^{(I,q)} + [\hat{f}_\chi^{(I,q)}] + [d_\chi^{(I,q)}]$, $[u^{(I)}] = [\underline{u}^{(I)}, \bar{u}^{(I)}]$. The set to be inverted by SIVIA is expressed as $\mathbb{Y}^{(I,q)} = [\xi^{(I,q)}] = 0$. Using the above information, the unknown interval box $[\hat{z}^{(I,q)}]$ can be estimated based on an initial prediction interval $[\hat{z}^{(I,q)}]_0 \triangleq [\underline{\hat{z}}_0^{(I,q)}, \bar{\hat{z}}_0^{(I,q)}]$. During the update phase and when a solution exists in the interval, forward-backward propagation contractors can be used. Thus, a solution box $[\hat{z}^{(I,q)}]_s$ is obtained by the union of all calculated interval boxes.

Remark 1: The bounds $\underline{\hat{z}}_0^{(I,q)}$, $\bar{\hat{z}}_0^{(I,q)}$ of the initial prediction of the interval can be deduced based on logic and physical laws

Remark 2: Forward-backward propagation contractors are preferred due to the high nonlinearity of the system [Jaulin et al. (2001)]

Using that $[\hat{z}^{(I,q)}]_s \triangleq [\underline{\hat{z}}_s^{(I,q)}, \bar{\hat{z}}_s^{(I,q)}] = y_z^{(I,q)} + [\hat{f}_z^{(I,q)}] + [d_z^{(I,q)}]$ and after some mathematical manipulations, the unknown interval $[\hat{f}_z^{(I,q)}] = [\underline{\hat{f}}_z^{(I,q)}, \bar{\hat{f}}_z^{(I,q)}]$ can be approximated as follows:

$$\begin{cases} \underline{\hat{f}}_z^{(I,q)} = y_z^{(I,q)} + \bar{d}_z^{(I,q)} - \bar{\hat{z}}_s^{(I,q)} \\ \bar{\hat{f}}_z^{(I,q)} = y_z^{(I,q)} - \bar{d}_z^{(I,q)} - \underline{\hat{z}}_s^{(I,q)} \end{cases} \quad (16)$$

The estimate of the sensor fault is finally obtained as:

$$\hat{f}_z^{(I,q)} = \frac{\bar{\hat{f}}_z^{(I,q)} + \underline{\hat{f}}_z^{(I,q)}}{2} D^{(I,q)}(t) \quad (17)$$

5. SIMULATION RESULTS

In this section, we apply the accommodation methodology described in Section 4 to a Diesel Engine using data from Geertsma et al. (2017) and the state-space modelling of the different interconnected subsystems shown in Section 3. The used model has already been validated in the aforementioned work using manufacturer and Factory Acceptance Test (FAT) data from the actual Diesel Engine. It is assumed that the measurements of each sensor of the engine are corrupted by uniformly distributed noise with $\bar{d}_j^{(I)}$ being 3 % of the amplitude of the noiseless measurements of the sensor. We have simulated permanent abrupt offset sensor faults affecting the torque sensor $S^{(2)}\{3\}$, the pressure sensor after the exhaust manifold $S^{(3)}\{1\}$ and the temperature sensor after the engine's compressor $S^{(4)}\{2\}$. The magnitude of the faults are chosen as $f_3^{(2)} = 5 \cdot 10^3\ Nm$, $f_1^{(3)} = 5 \cdot 10^4\ Pa$, $f_2^{(4)} = 100\ K$ and their times of occurrence at $T_{f3}^{(2)} = 10\ sec$, $T_{f1}^{(3)} = 10\ sec$ and $T_{f2}^{(4)} = 20\ sec$ respectively.

For the diagnosis of sensor faults, the distributed methodology described in [Kougiatsos et al. (2022)] is employed. The design gains of the various monitoring modules are selected as $L^{(1,1)} = 1.16$, $L^{(3,1)} = 445$, $L^{(4,1)} = 319.98$ while the learning rates for the design of the dynamic virtual sensors are selected as $\Gamma^{(1,1)} = 0.5$, $\Gamma^{(3,1)} = 8.7$, $\Gamma^{(4,1)} = 5$. The engine is simulated for 100 sec at its nominal operation point. Finally, the mean absolute percentage error for the sensor fault $f_*^{(I,q)}$, $(*) \in \{x, z\}$ in the module

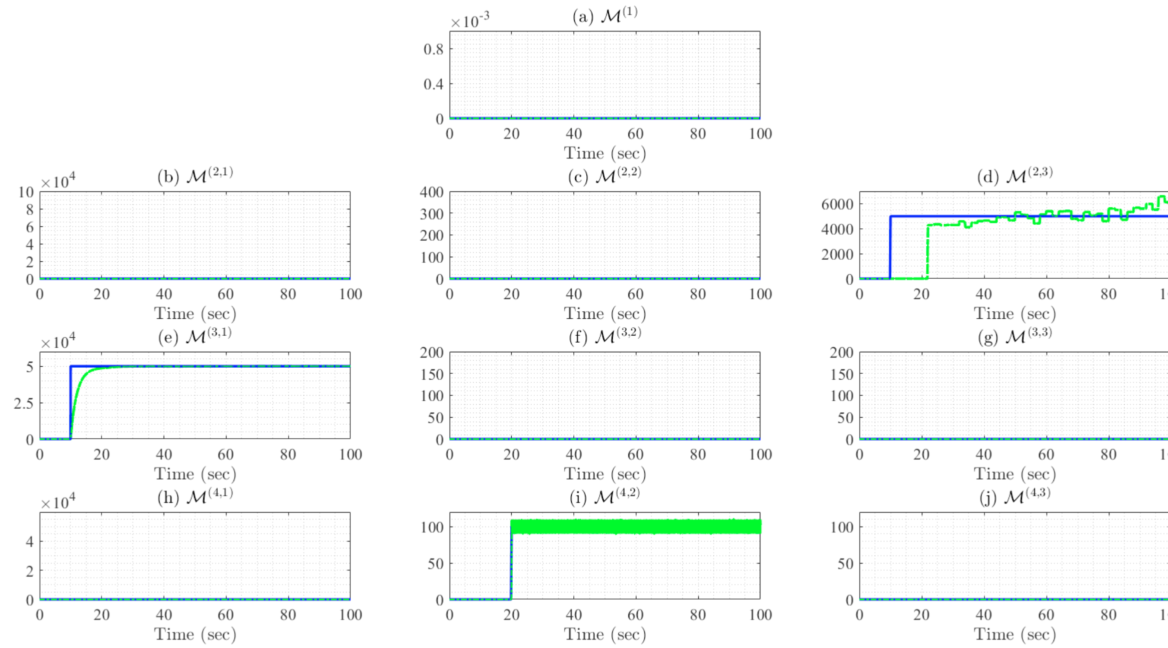

Fig. 3. Estimation of diagnosed sensor faults using the distributed virtual sensor scheme (blue line: actual fault, green line: fault estimation)

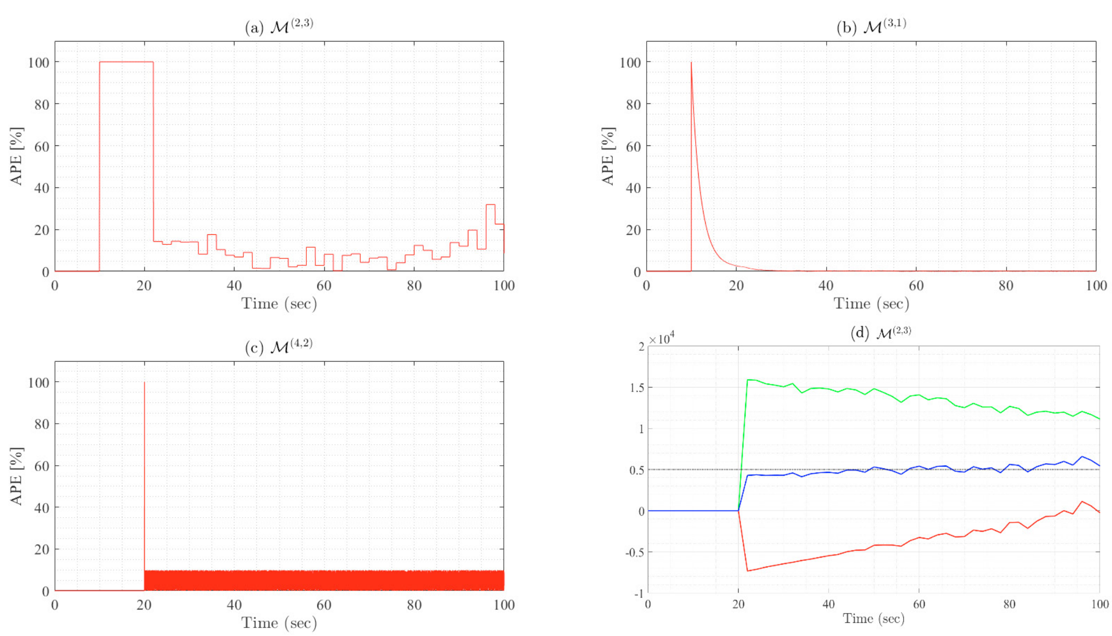

Fig. 4. (a)-(c) Absolute percentage errors [%] for the fault identification task and (d) Performance of algebraic sensor fault estimation using SIVIA-based virtual sensor (red line: $\underline{\hat{f}}_z^{(2,3)}$, green line: $\bar{\hat{f}}_z^{(2,3)}$, blue line: $\hat{f}_z^{(2,3)}$, black line: $f_z^{(2,3)}$)

$\mathcal{M}^{(I,q)}$, $(MAPE)^{(I,q)}$ is used as the benchmark for the proposed identification scheme.

The simulation results are shown in Figures 3 and 4. As can be seen from Fig.3(d), the virtual sensor based on SIVIA used as part of the monitoring module $\mathcal{M}^{(2,3)}$, manages to identify the magnitude of the actual fault affecting the sensor $\mathcal{S}^{(2)}\{3\}$ in 30 sec from the time the sensor fault was diagnosed. Here, it should be noted that the isolation is delayed by almost 10 sec. Nonetheless, a $(MAPE)^{(2,3)} = 8.76$ % is recorded starting from $t_0^{(2,3)} = 40$ sec, as can be seen from the trend in Fig.4(a). The interval estimation using SIVIA is also shown to converge, as expected, in Fig. 4(d) with the width of the interval $[\underline{\hat{f}}_z^{(2,3)}, \bar{\hat{f}}_z^{(2,3)}]$ getting gradually smaller and the center of the interval $\hat{f}_z^{(2,3)}$ converging to the actual simulated sensor fault $f_z^{(2,3)}$. Moreover, the adaptive differential estimator used as part of the monitoring module $\mathcal{M}^{(3,1)}$ also manages to identify the fault affecting the sensor $\mathcal{S}^{(3)}\{1\}$ within approximately 10 sec, as can be seen in Fig.3(e). The absolute percentage error value is also shown to converge in Fig.4(b) and assumes a $(MAPE)^{(3,1)} = 0.26$ % starting from $t_0^{(3,1)} = 20$ sec. Finally, the explicit algebraic estimator used as part of the module $\mathcal{M}^{(4,2)}$ almost instantly identifies the fault affecting the sensor $\mathcal{S}^{(4)}\{2\}$, as can be seen in Fig.3(i) and assumes a $(MAPE)^{(4,2)} = 3.74$ % starting from $t_0^{(4,2)} = 20$ sec, as can be seen from the trend in Fig.4(c). Based on the above results, the sensor faults are estimated with great accuracy by the virtual sensor scheme. In addition, the sensor fault effects are compensated so that they are not propagated to the neighbouring subsystems, as we can see from Fig.3(a)-(c),(f)-(h) and (j).

6. CONCLUSION

In this paper we presented a distributed virtual sensor scheme for reconstructing the measurements of diagnosed faulty sensors used for condition and operational monitoring of marine fuel engines. For each of the fuel engine's subsystems, monitoring agents were designed with the ability to actively compensate for sensor fault effects in those subsystems. To this end, a mixed scheme of virtual sensors was proposed for fault identification purposes due to the Differential-Algebraic nature of the system. More specifically, dynamic virtual sensors were proposed based on nonlinear estimators, static virtual sensors based on the explicit algebraic equations of the system and SIVIA-based virtual sensors based on the implicit algebraic equations of the system. The sensor measurements were then reconstructed by means of subtraction of the identified fault magnitudes from the original measurements. Finally, a good performance of the proposed methodology in identifying and alleviating the effects of multiple simultaneous sensor faults has been suggested by the simulation results. Future work will include the sensitivity analysis of the proposed methodology with respect to the magnitudes of sensor noise and design gains.

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