

A Frequency-Domain Framework for Sensor Fault Diagnosis in Vibration-Based SHM: Application to a Population of Composite Aerostructures under Operational Uncertainty

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Abstract. Reliable sensor fault diagnosis is critical for high performance vibration-based Structural Health Monitoring (SHM) where a network of accelerometers is typically used. The problem is compounded when SHM is performed for a population of nominally identical composite aerostructures where manufacturing and operational uncertainty may not only significantly affect the vibration measurements and obscure early-stage structural faults but also render sensor fault detection unreliable. Building on a recently introduced frequency-domain framework for fault detection in a single vibration sensor, this study presents an extension of the employed methodology for sensor fault diagnosis including, beyond detection, sensor fault type identification and faulty sensor isolation from the network. The methodology is based on indices constructed using the sensors' Multiple Coherence, as well as the Transmittance Functions (TFs) obtained from a Multiple-Input Single-Output TF AutoRegressive with eXogenous (MISO-TF-ARX) input model. The performance of the methodology is assessed through thousands of test cases using acceleration signals from a network of 3 sensors obtained from an Abaqus-based finite element model of a composite beam under population-induced, temperature and excitation variability. The results show an overall fault detection accuracy of 98.16%, with fault type identification rates of 88.23%, 94.32%, and 95.06% for bias, gain and precision degradation faults, respectively, while faulty sensors are overall isolated for the 92.54% of the considered test cases.

Key words: Sensor Fault Diagnosis, Vibration-based SHM, Operational Uncertainty, Population of Composite Aerostructures, Statistical Time Series Methods

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1 INTRODUCTION

Sensor fault diagnosis, which includes fault detection, type identification, and isolation of the faulty sensor from the network, is critical for ensuring the high effectiveness and reliability of a vibration-based SHM system that typically employs a network of accelerometers [1]. A bias, gain or other types of sensor fault may mislead the SHM system and significantly increase the false alarms rate. This issue becomes highly challenging when similar sensor networks are installed in a fleet of aircraft for SHM of a population of nominally identical composite aerostructures. The uncertainty in the measurements due to variability in manufacturing, environmental and operating in-flight conditions, may obscure corresponding effects from early stage sensor faults, and thus degrade the SHM system's diagnosis performance.

Based on the type of the employed modelling of the healthy sensor network, the current methods addressing the problem may be classified as '*single-sensor*' or '*multi-sensor*'.

Single-sensor methods use one model per sensor of the network representing its healthy state. Cumulative Sum Control Chart (CUSUM) [2] based methods have been employed for detecting drift in displacement measurements. Deep learning-based methods, including Convolutional Neural Networks (CNN) [3] and Stochastic Gated Recurrent Neural Networks (SG-RNN) [4], have been used for the supervised detection and type identification of a broader range of sensor faults such as bias, gain, and precision degradation in acceleration measurements under uncertainty due to measurement noise.

On the other hand, *multi-sensor methods* relying on the statistical correlations among vibration responses from different sensors of the network, aim to construct a single model that represents the healthy state of the entire network. Methods based on variants of the Principal Component Analysis (PCA) [5, 6] and Independent Component Analysis (ICA) [7] have been extensively utilized for the detection and identification of bias, drift, and gain in acceleration and displacement measurements under operational uncertainty and measurement noise. Alternatively, variants of the Minimum Mean Square Error (MMSE)-based approach [8] have been used for the identification of bias, drift, gain, and precision degradation faults in acceleration measurements of a sensors network. The distinction between sensor faults and temperature effects has been addressed through PCA-based dimensionality reduction of the log-likelihood ratio [9]. In the same context, a virtual sensor may be developed based on a Multi-Layer Back-propagation Neural Network (MLP), trained to represent the healthy state of each sensor in the network by utilizing measurements from all sensors [10]. Sensor fault detection for acceleration measurements is achieved examining deviations on the residuals between the actual sensors output and the corresponding virtual sensor predictions. Deviations in the form of residuals have also been used for sensor fault detection in strain measurements using AutoRegressive with eXogenous inputs (ARX) stochastic models to sensor pairs [11]. While such an approach has shown effectiveness in detecting sensor drift, bias, spikes, precision degradation, and exponential sensor faults, it is challenged in selecting the optimal sensor pairs within the network. The interdependencies among measurements from different sensors may inhibit accurate modelling, while ensuring robustness to variability caused by multi-acting, variable, excitations remains a

significant challenge.

However, there are several limitations in the above studies: (a) typically, only a single uncertainty factor, such as temperature, noise, or excitation, is considered; (b) the achievable performance remains sensitive to multi-acting excitation conditions and variability in the excitation profile; (c) the methods' performance evaluation is often not systematic, frequently based on limited measurements from faulty sensors within the network; (d) the considered sensor faults cause substantial deviations in time-domain responses that are not representative of those observed under realistic fault conditions.

To address these limitations, a novel, robust to varying environmental and multi-acting excitation conditions, frequency-domain framework for sensor fault detection and type identification in a single accelerometer that is used for SHM in a population of composite aerostructures has been recently presented by some of the present authors in [12]. This framework is based on appropriate indices founded on Transmittance Functions (TFs), as obtained from a Multiple-Input Single-Output Transmittance Function AutoRegressive with eXogenous (MISO-TF-ARX) input model, and Multiple Coherence function, which ensure independence from, and thus robustness to, multi-acting excitation conditions and variability in the excitation profile.

The present study aims at extending the above frequency-domain framework for fault diagnosis in a network of multiple sensors employed for SHM, and assessing its effectiveness by addressing the following key research questions:

- Is it possible to reliably detect a fault at any sensor of the network with high accuracy, under the presence of significant uncertainty caused by manufacturing, temperature and multi-acting excitation variability?
- To what extent can the framework correctly identify the type of sensor fault (Bias, Gain, or Precision Degradation) and accurately isolate the faulty sensor within the network?

The postulated framework is assessed using acceleration signals from a three sensors network implemented through a finite element model of a composite UAV tail boom. The model represents the healthy dynamics of the aerostructure under significant uncertainty caused by population-induced manufacturing variability, temperature fluctuations and different excitation profiles. Bias, Gain, and Precision Degradation sensor faults are investigated, each applied at three different magnitudes to any sensor of the network. This results in a total of 27 fault scenarios, 135 test cases per sensor state (healthy, three magnitudes for each fault type), yielding a total of 3 645 test cases. The results are provided in terms of correct classification rates for all levels (detection, type identification, isolation) of sensor fault diagnosis.

2 THE FREQUENCY-DOMAIN FRAMEWORK FOR AUTOMATED MULTIPLE SENSOR FAULT DIAGNOSIS

2.1 The fault diagnosis characteristic quantities

Given a network of m accelerometers installed on the considered structure, a total of m Multiple Coherence (MC) functions are obtained. In each MC function a distinct accelerometer

acts as the output while the remaining ones as pseudo-inputs. The MC function for the s -th accelerometer when this is considered as the output is given by:

$$\gamma_{y_s|\mathbf{x}_s}^2(f) = \frac{S_{y_s\mathbf{x}_s}^*(f) \cdot S_{\mathbf{x}_k\mathbf{x}_s}^{-1}(f) \cdot S_{y_s\mathbf{x}_s}(f)}{S_{y_sy_s}(f)} \quad (1)$$

where $\mathbf{x}_s = [y_1[t], \dots, y_{s-1}[t], y_{s+1}[t], \dots, y_m[t]]^T$ is the $(m-1)$ -dimensional pseudo-input vector, excluding the s -th sensor, and $S_{y_s\mathbf{x}_s}$, $S_{\mathbf{x}_k\mathbf{x}_s}$, and $S_{y_sy_s}$ represent the Cross and Auto Power Spectral Densities (CPSD and PSD) of the vibration signals (see details in [12]). The MC function is the characteristic quantity that is used for the diagnosis of sensor precision degradation as described in the next subsection, while the Transmittance Functions (TFs) of a stochastic MISO-TF AutoRegressive with eXogenous (MISO-TF-ARX) model of orders n_a, n_b are employed for the diagnosis of sensor bias and gain fault for each sensor. The general form of the MISO-TF-ARX model is [12]:

$$y_s[t] + \sum_{i=1}^{n_a} a_i^s \cdot y_s[t-i] = \sum_{\substack{j=1 \\ j \neq s}}^{m-1} \sum_{i=1}^{n_b} b_i^{j,s} \cdot y_j[t-i] + w_s[t], \quad w_s[t] \sim \text{i.i.d. } \mathcal{N}(0, \sigma_w^2) \quad (2)$$

where $t = 1, \dots, N$ represents the discrete-time normalized by the sampling period T_s , $w_s[t]$ the model residual signal, i.i.d. stands for independent and identically distributed, and $\mathcal{N}(0, \sigma_w^2)$ indicates normal (Gaussian) distribution with zero mean and variance σ_w^2 . a_i^s ($i = 1, \dots, n_a$) indicate the parameters of the model AutoRegressive (AR) part for the s -th sensor (used as output), while $b_i^{j,s}$ with $i = 1, \dots, n_b$ and $j = 1, \dots, m-1$ the corresponding parameters of the eXogenous (X) part associated with the pseudo-inputs. Using the backshift operator $\mathcal{B}$ ($\mathcal{B}^j \cdot x[t] = x[t-j]$), the model is rewritten as:

$$A^s(\mathcal{B}) \cdot y_s[t] = \sum_{\substack{j=1 \\ j \neq s}}^{m-1} B^{j,s}(\mathcal{B}) \cdot y_j[t] + w_s[t] \quad (3)$$

$$\text{where } A^s(\mathcal{B}) \triangleq 1 + a_1^s \cdot \mathcal{B} + \dots + a_{n_a}^s \cdot \mathcal{B}^{n_a}, \quad B^{j,s}(\mathcal{B}) \triangleq b_1^{j,s} \cdot \mathcal{B} + \dots + b_{n_b}^{j,s} \cdot \mathcal{B}^{n_b} \quad (4)$$

Based on the above, the following transmittance functions may be obtained:

$$TF_{j,s}(\mathcal{B}) = \frac{B^{j,s}(\mathcal{B})}{A^s(\mathcal{B})}, \quad j \neq s, \quad s = 1, \dots, m. \quad (5)$$

The model parameter vector corresponding when each sensor is used as output is estimated using Ordinary Least Squares [13, pp. 204-205]:

$$\boldsymbol{\theta}_s := [a_1^s \dots a_{n_a}^s : b_1^1 \dots b_{n_b}^1 : b_1^{m-1,s} \dots b_{n_b}^{m-1,s}]^T. \quad (6)$$

while model orders n_a and n_b selection and validation are based on a standard identification procedure, based on the minimization of the Bayesian Information Criterion (BIC) and Residual to Series Sum of Squares (RSS/SSS), as well as residual whiteness testing [13, pp. 505-514].

2.2 Sensor Fault Diagnosis

2.2.1 Baseline phase

During the baseline phase, a set of vibration signals from the m sensors are obtained from the considered structure under healthy sensor state. These signals are used for the estimation of the m MC functions and the $(m - 1)$ Transmittance Functions derived from the corresponding m MISO-TF-ARX(n_a, n_b) models. Subsequently, the following indices are computed for each sensor ($s = 1, \dots, m$), within properly selected frequency ranges $[f_{\min}^{\mathcal{FT}}, f_{\max}^{\mathcal{FT}}]$ Hz wherein the effects of each fault type $\mathcal{FT}$, ($\mathcal{FT} = B$ for Bias fault, $\mathcal{FT} = G$ for Gain fault, $\mathcal{FT} = PD$ for Precision Degradation) are expected to be evident ($j = 1, \dots, m - 1, j \neq s$):

$$\mathcal{F}_{j,s}^B = \sum_{f=f_{\min}^B}^{f_{\max}^B} \left| \|TF_{j,s}(f + \delta f)\| - \|TF_{j,s}(f)\| \right|, \quad \mathcal{F}_{j,s}^G = \int_{f_{\min}^G}^{f_{\max}^G} \|TF_{j,s}(f)\| df \quad (7)$$

$$\mathcal{F}_s^{PD} = \int_{f_{\min}^{PD}}^{f_{\max}^{PD}} \gamma_{y_s|x_s}^2(f) df \quad (8)$$

where $\|\cdot\|$ stands for magnitude of the Transmittance function and δf denotes a selected increment in frequency. For each sensor $s = 1, \dots, m$ serving as the output, a low $f_L^{\mathcal{FT}}$ and a high threshold $f_H^{\mathcal{FT}}$ are determined for each of the above indices. Thus, different ranges $R_{j,s}^B$ and $R_{j,s}^G$ are determined for the indices used to detect sensor bias and gain, respectively, within which the indices should lie under healthy state, while the range R_s^{PD} is determined for precision degradation.

It is noted that $\mathcal{F}_{j,s}^B$ detects the slope change in the low-frequency range induced by the bias-related offset in the DC gain, $\mathcal{F}_{j,s}^G$ the overall variation (increase or decrease) of the TF magnitude in the considered bandwidth due to gain variations, and $\mathcal{F}_s^{PD}$ the coherence reduction arising from increased measurement noise.

2.2.2 Inspection Phase

Sensor fault detection. During the inspection phase and once a new set of signals is available from the considered structure under unknown sensor state, the indices of Equations (7) and (8) are determined and their values are examined if they lie in the corresponding ranges from the Baseline phase through the following hypothesis testing:

$$\begin{aligned} \mathcal{H}_0 : & \quad \mathcal{F}_{j,s}^B \in R_{j,s}^B \text{ and } \mathcal{F}_{j,s}^G \in R_{j,s}^G \text{ and } \mathcal{F}_s^{PD} \in R_s^{PD}, \forall j, s \quad \text{Healthy Sensors} \\ \mathcal{H}_1 : & \quad \text{Else} \quad \text{At least one sensor is faulty} \end{aligned} \quad (9)$$

Sensor fault type identification and isolation. Once a sensor fault has been detected, the identification of its type is achieved through the following rule :

$$\begin{aligned} \text{If: any of } \mathcal{F}_{j,s}^B \notin R_{j,s}^B \text{ and } \mathcal{F}_{j,s}^G \in R_{j,s}^G \text{ and } \mathcal{F}_s^{PD} \in R_s^{PD}, \forall j, s & \rightarrow \text{Bias Fault} \\ \text{If: any of } \mathcal{F}_{j,s}^G \notin R_{j,s}^G \text{ and } \mathcal{F}_{j,s}^B \in R_{j,s}^B \text{ and } \mathcal{F}_s^{PD} \in R_s^{PD}, \forall j, s & \rightarrow \text{Gain Fault} \\ \text{If: any of } \mathcal{F}_s^{PD} \notin R_s^{PD}, \forall s & \rightarrow \text{Precision Degradation} \end{aligned} \quad (10)$$

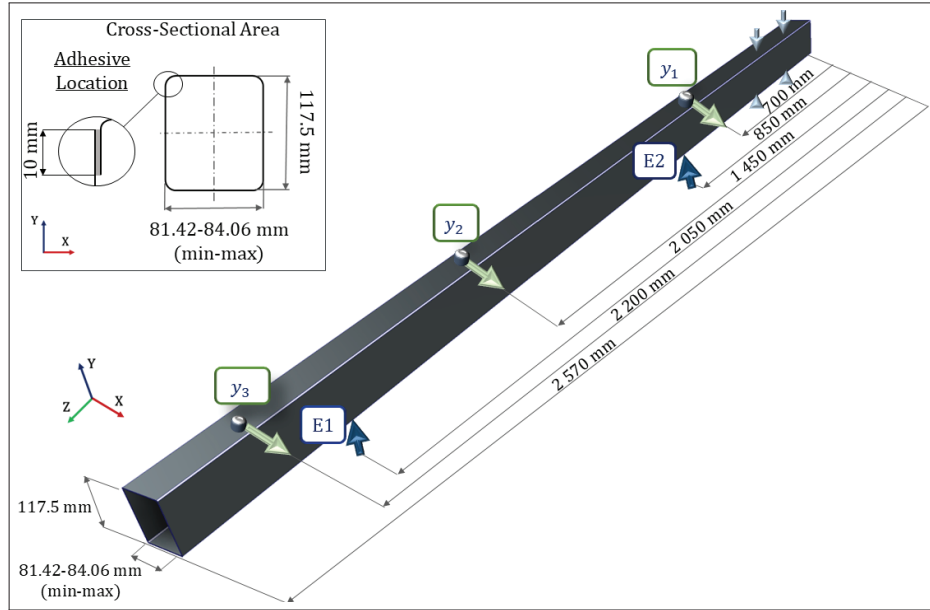


Figure 1: Schematic representation of the finite element representation of the UAV tail boom, the excitation positions ($E1$, $E2$) and the acceleration sensors y_1 / y_2 / y_3 .

Fault isolation is achieved simultaneously through the above procedure. In particular, if the fault is of the bias or gain type, then *all* of the corresponding indices, where the faulty sensor participates either as pseudo-input j or output s , will lie outside its range defined during the baseline phase. In the case of precision degradation fault type, the sensor s that yields the minimum value of $\mathcal{F}_s^{PD}$ is isolated as the faulty from the network.

3 THE COMPOSITE AEROSTRUCTURE, THE UNCERTAINTY FACTORS AND THE SENSOR FAULTS

3.1 The finite element representing the healthy dynamics of the composite aerostructure

A bonded spar model of a UAV tail boom, consisting of two C-shaped carbon-epoxy webs and two skins of varying thickness bonded with adhesive to form a closed rectangular beam (see Figure 1), has been implemented in Abaqus using a finite element (FE) model. The structure has nominal dimensions of $2570 \times 82.74(\pm 1.32) \times 117.5$ mm, with a ply thickness of 0.22 mm per lamina, and material properties under the healthy state and nominal temperature ($T = 20^\circ\text{C}$) are provided in Table 1. Quad shell elements have been used for the webs and skin, and brick elements for the adhesive, with mesh sizes of 5×5.136 mm and $5 \times 0.2 \times 0.588$ mm, respectively, totaling approximately 187 098 elements and 150 383 nodes. The structure is considered under fixed-free boundary conditions, with bolts placed at 20 mm and 313 mm from the edge to simulate fuselage attachment.

The acceleration measurements have been acquired in the transverse direction near the root (y_1), center (y_2), and tip (y_3) under multi-acting vertical excitation (E_1 and E_2). The excitation

Table 1: Experimentally measured temperature dependence of the material properties for the nominal composite aerostructure under healthy state.

T (°C)	Carbon Epoxy				Adhesive	Damping
	E_{11} (GPa)	E_{22} (GPa)	G_{12} (GPa)	ν_{12}	G_{12} (GPa)	ζ (%)
-40	58.0	58.0	4.27	0.08	0.584	0.80
20	57.8	56.2	3.87	0.07	0.393	0.48
60	57.9	57.9	3.38	0.07	0.147	1.34

For each simulation, a temperature $T \sim U[-50, 70]$ °C is generated; the corresponding material properties are obtained via quadratic interpolation of the above values at each generated T .

signals have been discretized at an initial sampling frequency of $f_s = 40\,000$ Hz and subsequently filtered using a low-pass Chebyshev Type II filter; $f_{stop} = 2\,000$ Hz (cut-off), order $n = 24$. The Mode Superposition method has been employed, incorporating all modes within the frequency range of $[0, 2\,000]$ Hz. A constant time step of $\Delta t = 2.5 \times 10^{-5}$ s (integration frequency: $f_{int} = 40\,000$ Hz) has been used, yielding an initial signal length of 100 000 samples. The response signals have subsequently been resampled at $f_s = 4\,000$ Hz, resulting in a final signal length of $N = 10\,000$ samples with duration of 2.5 s.

3.2 The uncertainty factors

The performance and robustness of the sensor fault diagnosis frequency-domain framework is investigated under multiple uncertainty factors that affect the obtained acceleration measurements. These factors include: (i) operating temperature variability in the range of $[-50, 70]$ °C, (ii) manufacturing variability affecting skin and adhesive material properties, and (iii) varying excitation profiles due to different operational states and multi-acting excitations.

The variability of the material properties due to temperature uncertainty – including the longitudinal modulus (E_{11}), transverse modulus (E_{22}), and in-plane shear modulus (G_{12}) of the carbon-epoxy (webs and skin), the shear modulus (G_{12}) of the adhesive, and the damping ratio (ζ) – is modelled using temperature samples drawn from uniform distributions within the range $[-50, 70]$ °C (see details in [14]). These samples are then used for quadratic interpolation of the corresponding material properties based on their experimentally measured temperature dependence for the nominal structure and damping [14], as provided in Table 1.

For each considered temperature sample, manufacturing variability is further implemented via three uniform distributions within the range $[-10, 10]\%$. These distributions are applied to the longitudinal, transverse, and shear moduli (E_{11} , E_{22} , G_{12}) of the skin, as well as to the shear modulus (G_{12}) of the adhesive so as each numerical experiment has a unique realization.

In addition, each member is subjected to one of the two multi-acting excitation profiles: P1, a band-limited white noise within $[0, 2\,000]$ Hz; P2, a colored noise generated via an Auto-Regressive (AR) model of order $n = 6$, incorporating engine effects (see details in [14]). Distinct seed numbers are assigned for noise generation at each excitation point to ensure variability.

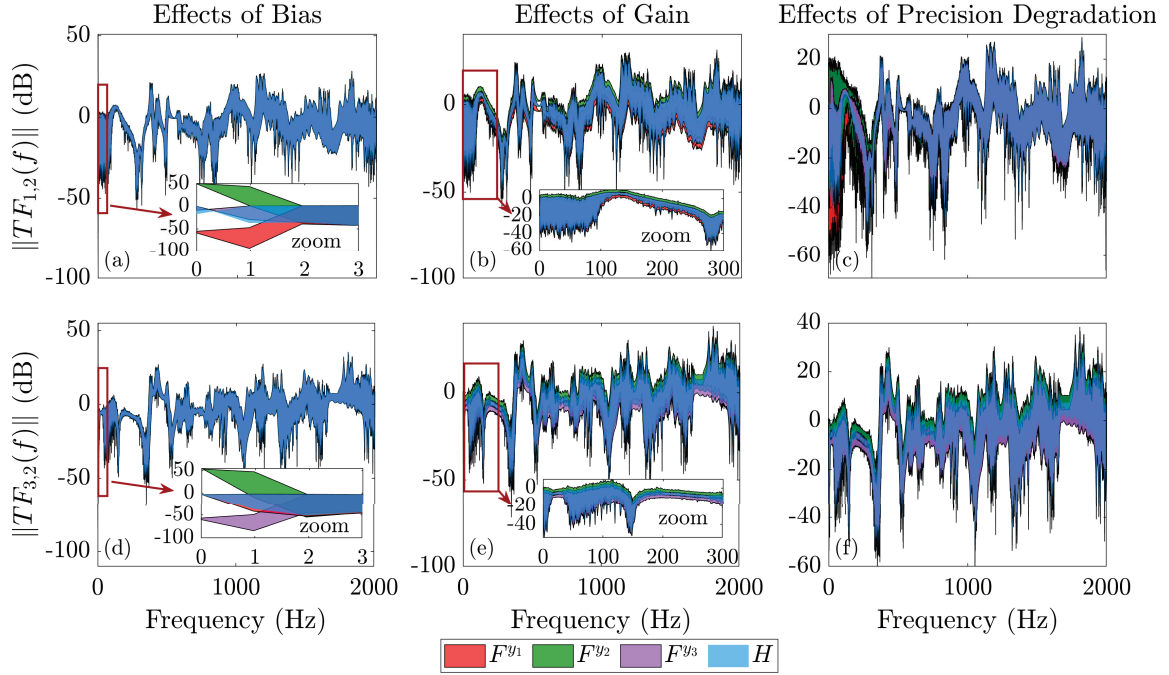


Figure 2: Welch-based MISO-TF envelope magnitude estimates using the sensor y_2 as output and y_1, y_3 as pseudo-inputs. (a) – (c) $TF_{1,2}$ and (d) – (f) $TF_{3,2}$ including healthy sensors (blue envelopes) and the small magnitude of the considered faults in sensor y_1 (red envelopes), y_2 (green envelopes) and y_3 (purple envelopes); Healthy sensors: 135 test cases, Faulty sensors: 135 test cases per fault type, Excitation profiles: both P1 and P2 are used.

ity, with all signals filtered to the above frequency bandwidth using a low-pass Chebyshev Type II filter. The robustness of the framework under excitation profile uncertainty is achieved with measurements obtained under P1 profile in the Baseline phase, while both P1 and P2 profiles are used in the Inspection phase.

3.3 The sensor faults and their effects on the signals

Three distinct sensor fault types, as defined in [8, 12], are considered in this study: (i) Bias (B), (ii) Gain (G), and (iii) Precision Degradation (PD). Each fault persists over the entire duration of the measured signal ($N = 10\,000$ samples). For each fault type, three fault magnitudes ($\mathcal{FM}$) are implemented: Small (S), Medium (M), and Large (L).

In particular, the Bias fault in the measurement is implemented via the equation $y_B[t] = y[t] + \alpha\sigma_y$, where α denotes the fault magnitude that takes the values of 2%, 5%, and 10% corresponding to Small, Medium, and Large, respectively, and σ_y is the standard deviation of the measurement under the healthy sensor state. Gain fault is implemented via the $y_G[t] = \alpha y[t]$, where α takes values of 0.7 (S), 1.4 (M), and 0.5 (L). For Precision Degradation faults, the expression $y_{PD}[t] = y[t] + e[t]$ is used, where $e[t]$ represents the sensor noise that is $e[t] \sim \mathcal{N}(0, \sigma_e^2)$, while the noise-to-signal ratio (NSR) is set to 2% (S), 5% (M), and 10% (L). In

Table 2: Sets of vibration signals used in the baseline and inspection phases.

Sensor State	# of Beams under Manuf. Variab.	# of Temperatures under $P1/P2$	# of Signal Sets under $P1/P2$	# of Signal Sets per $\mathcal{FM}^*$
Baseline Phase				
Healthy	9	12/0	108/0	—
Inspection Phase				
Healthy (H)	9	10/5	90/45	—
Faulty [◊] (F^{y_i})	9	10/5	90/45	135
[◊] : $\mathcal{FM} = S/M/L$ fault magnitude; *: Faulty sensor $i = 1/2/3$ under fault type $B/G/PD$ Total # of inspection test cases: 135/3 645 under healthy/faulty sensor state (135 per sensor, fault type and magnitude).				

total, 9 faults are considered, each applied to any of the three sensors network, which results in 27 distinct fault scenarios.

Non-parametric Welch-based magnitude estimates of the MISO TFs [15] $TF_{1,2}$ and $TF_{3,2}$ under all uncertainty factors, are provided in Figure 2 using sensor y_2 as the output. In particular the TFs of the healthy (H) sensors state are depicted, along with those affected by the small sensor faults on each of the three sensors y_1 , y_2 and y_3 , designated as F^{y_1} , F^{y_2} and F^{y_3} , respectively. Based on these graphs, the following observations are made: (a) the effects of the uncertainty factors on the measured dynamics under the healthy sensor state lead in a significant overlap between the healthy and faulty sensors conditions, indicating a challenging sensor fault detection problem; (b) the impact of bias fault is evident only within the frequency range of $[0, 2]$ Hz, highlighting the need for accelerometers capable of accurate measurements in this range; (c) the weak effects of the considered gain and precision degradation small faults are shown in almost the entire range of $[0, 2000]$ Hz; (d) the faults in sensor y_2 (used as output) affect the magnitude of both TFs. On the other hand, when a sensor fault affects any of the pseudo-inputs (y_1 and y_3 in this figure), the impact is limited only to the TF where the sensor contributes. For instance, in Figures 2(a), (d) the corresponding faults in y_3 and y_1 are not evident. All the above points underscore the significant challenges involved in sensor fault diagnosis under combined uncertainty.

4 SENSOR NETWORK FAULT DIAGNOSIS RESULTS

Baseline phase. The training of the postulated frequency-domain framework is conducted using $n = 108$ sets of vibration response signals obtained from the considered three sensors network. The signals are collected from 9 randomly selected healthy aerostructures within the population. The operating conditions vary, as previously mentioned, including different excitation realizations of profile P1 and 12 randomly chosen temperature conditions as shown in Table 2. Based on these, 3×108 MISO-TF-ARX(200,200) models of Equation (2) and 3×108 MC functions of Equation (1) (one model/function per sensor) are estimated. The Welch method with Hamming window of 4096 samples and 90% overlap is used for the MC functions. The indices of Equations (7), (8) are then obtained. Based on these, the ranges

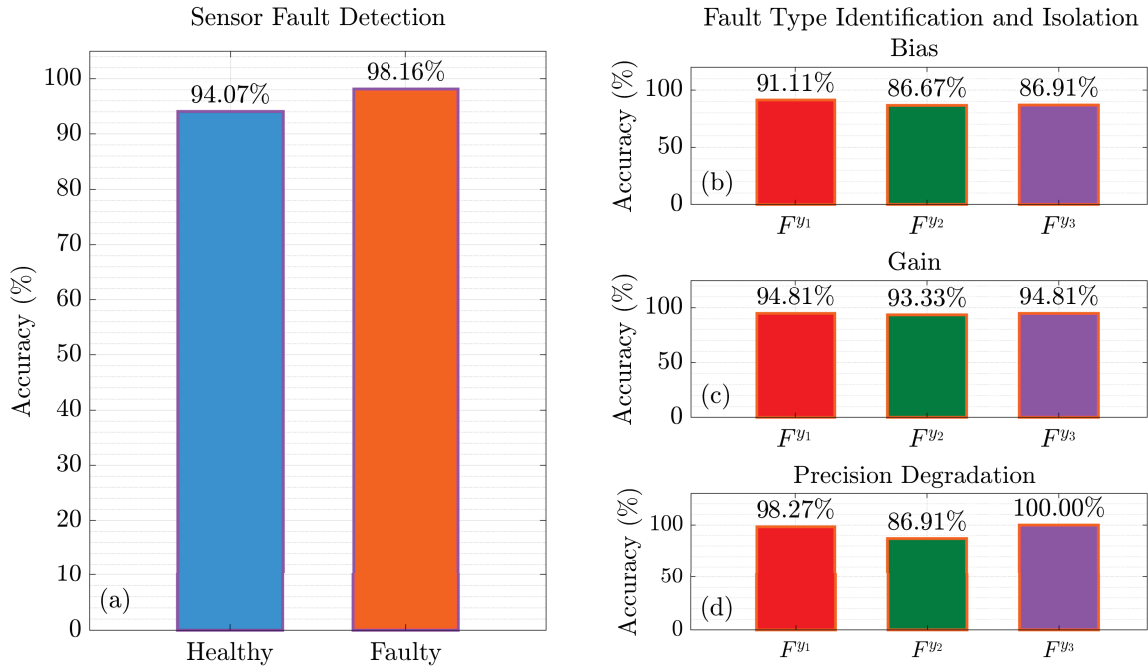


Figure 3: Sensor fault diagnosis results (inspection phase) in terms of correct classification rate (Accuracy). These results are based on 135 test cases under healthy sensor state and 405/405/405 test cases per faulty sensor $y_1/y_2/y_3$ under Bias/Gain/Precision Degradation; 135/3 645 test cases under healthy/faulty sensor state in total.

$[f_{min}^{FT}, f_{max}^{FT}]$ are determined for each considered sensor fault type as: $[f_{min}^B, f_{max}^B] = [0.07, 0.15]$ Hz using $\delta f = 0.01$ Hz, $[f_{min}^G, f_{max}^G] = [0.07, 300]$ Hz and $[f_{min}^{PD}, f_{max}^{PD}] = [87, 140]$ Hz. Based on the lower and upper thresholds $[l_L^{FT}, l_H^{FT}]$ of the indices within the above frequency ranges, the $R_{j,s}^B, R_{j,s}^G, R_s^{PD}$ ranges are determined as described in Section 2.2.1 by using each sensor in the network as output with the remaining sensors used as pseudo-inputs in each case.

Inspection phase. The assessment of the postulated framework is conducted using additional vibration response (see Table 2) signal sets obtained from 9 healthy aerostructures not included in the Baseline phase. Each structure is subjected to 10 randomly selected temperature conditions and both excitation profiles P1 and P2, resulting in 90/45 simulations under P1/P2, respectively. Each simulation in this phase is considered under both healthy sensor state and each of the 27 sensor fault scenarios, resulting in 135/3 645 inspection test cases (Table 2) under healthy/faulty sensor states, respectively. Classification accuracy rates are then computed to assess the performance of the frequency-domain framework in terms of sensor fault detection, type identification, and faulty sensor isolation.

The sensor fault diagnosis results are provided in Figure 3. In particular, *sensor fault detection* (Figure 3(a)) leads to 94.07% of correct classification for the considered healthy and 98.16% for the faulty sensor test cases, indicating very good performance. Regarding *sensor fault type identification and isolation* results and following the procedure of Section 2.2.2 where sensor fault type identification and isolation is simultaneously achieved, the method achieves

similarly very good results. Based on Figure 3(b) the average correct fault type identification rate for the Bias fault is 88.23%, while this rate is 94.32% for Gain and 95.06% for Precision Degradation. On the other hand, based on the left part (red bars) of Figures 3(b)-(d), the average correct fault isolation rate for sensor y_1 is 94.73%, while this rate is 88.97% (green bars) and 93.91% (purple bars) for sensors y_2 and y_3 , respectively, leading to a remarkable overall sensor fault isolation of 92.54%.

5 CONCLUSIONS

The study's main conclusions, in response to the questions outlined in the introduction, may be summarized as follows:

- Despite the presence of significant uncertainty, a high fault detection rate has been achieved by the postulated frequency-domain framework with accuracy rates of 94.07% and 98.16% for the healthy and faulty sensor states, respectively.
- High accuracy has been also achieved in fault type identification, with classification rates of 88.23%, 94.32%, and 95.06% for Bias, Gain, and Precision Degradation faults, respectively. The postulated framework has demonstrated strong capability in isolating the faulty sensor in the network, with an overall isolation accuracy of 92.54%.

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