Modular Distributed Fault Diagnosis for Adaptive Structures using Local Models ⋆

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Abstract: Adaptivity has become a promising concept in civil engineering to improve the load-bearing behavior of buildings and to reduce material consumption. However, the integrated actuators and sensors increase the complexity and adversely affect the reliability making a fault diagnosis for actuator and sensor faults necessary. In this paper, the distributed fault diagnosis of an adaptive high-rise truss structure, which is characterized by a modular design, is investigated. Based on local models and the local measurement information of hydraulic actuators and strain gages, a distributed fault diagnosis scheme is proposed for the diagnosis of actuator and sensor faults. Since the local models do not have information about the interconnection to other modules, the model-based residual is uncertain and faults in the other module can affect the local residual. For this reason, an effective online estimation of the probability density function and the Kullback-Leibler divergence of the residual is presented for change detection considering the stochastic uncertainties. Moreover, the selected sensor layout of the adaptive structure allows the isolation of the investigated actuator faults such that fault propagation paths of the distributed system are analyzed and sensor faults are isolated by communicating the detected changes in the modules. The effectiveness of the approach is illustrated in a simulation study.

Keywords: Applications of FDI and FTC, Distributed Fault Diagnosis, Statistical methods/signal analysis for FDI, Smart Structures, Building Automation

1. INTRODUCTION

According to recent studies of the OECD (2015), the building sector is a major contributor to the world-wide energy demand, material consumption and emissions. This is related to the state-of-the-art design of buildings, which are designed to withstand high, but rarely occurring loads. Adaptive structures are able to react to external loads and represent a promising approach in civil engineering to enhance the load-bearing behavior of a structure, see Korkmaz (2011). Thus, the material and energy consumption is reduced significantly, since the embodied energy is partially replaced by operational energy in case of high loads, see Sobek and Teuffel (2001). However, integrating actuators, sensors and controllers into the structure affects its reliability and safety, which are highly relevant for civil structures. For this reason, the fault diagnosis of actuator and sensor faults are an essential part of adaptive civil structures.

In this paper, the fault diagnosis for a high-rise adaptive truss structure, which is illustrated in figure 1, is addressed. The steel construction has a height of 36 meter and is accessible by a stair tower. The structure has a modular design and consists of four modules. The lower modules are equipped with strain gages as well as hydraulic actuators in selected elements which are controlled by a local computational unit in the module. The actuator and sensor placement in adaptive-high rise structures regarding controllability and observability are addressed by Heidingsfeld et al. (2017) respectively Rapp et al. (2017).

The modular design, the distributed computational units as well as the scale of the system motivate the application of a modular

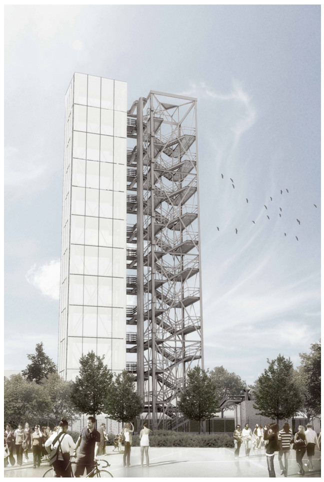

Fig. 1. Rendering of the high-rise adaptive truss structure with access tower at the Campus of the University of Stuttgart, Germany. Source: ILEK, University of Stuttgart

and distributed fault diagnosis algorithm, which is able to detect faults in the strain gages and hydraulic actuators of each module and only relies on a local model of the module. Therefore, the modular fault diagnosis does not rely on a model of the overall structure and the fault diagnosis within the modules can be reused for arbitrary connections of the modules.

In the literature, a variety of model-based and data-based approaches for the centralized as well as distributed fault diagnosis exist. Model-based approaches require an accurate physical model of the system, which is used for deriving residuals using parity equations or observer schemes. Data-based approaches

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do not rely on a physical model but on a sufficient amount of training data for applying methods like principal component analysis (PCA), partial least squares or neural networks.

The research for distributed fault diagnosis techniques is growing due to the increasing complexity and scale of systems as well as the scalability issues of centralized approaches, for example in sensor networks, see Dong et al. (2014). Many model-based distributed fault diagnosis algorithms have been developed for discrete-event systems, see e.g. Baroni et al. (1999) but also many linear and nonlinear continuous-time systems, see e.g. Ferrari et al. (2012), Boem et al. (2013), have been proposed in the literature. The most common approach for the definition of a set of lower order subsystems from the overall system dynamics is the application of decomposition techniques based on the structural graph such that local observers in each subsystem are realized. The different subsystems communicate by exchanging information like measurements, see Shames et al. (2011), Ferrari et al. (2012), state estimates, see Zhang and Zhang (2012) as well as fault signatures, see Daigle et al. (2007). Data-based distributed methods comprise for example multiblock analysis, see e.g. Qin et al. (2001), weighted-least squares, see Marelli and Fu (2015), canonical correlation analysis, see Jiang et al. (2017), or principal subspace estimation, see Li et al. (2011).

For smart and adaptive structures, mainly centralized approaches have been investigated so far. Sharifi et al. (2010) uses a PCA-based sensor fault isolation and detection method for smart structures, which is applied to a three-story building structure equipped with a magnetorheological damper. For adaptive shell structures with hydraulic actuation, Heidingsfeld et al. (2014) investigated dedicated observer schemes for sensor fault diagnosis in the strain gages. A centralized detection and isolation of sensor and actuator faults in adaptive high-rise structures, as investigated in this work, is presented in Gienger et al. (2020b), where parity equations are combined with PCA to consider unknown stochastic disturbances. In Gienger et al. (2020a), deep convolutional neural networks are investigated for centralized fault diagnosis as well as decentralized fault diagnosis based on the different sensor systems for the investigated adaptive high-rise structure.

In this work, the subsystems are already predefined by the modules and local models of each module are available. Due to the unknown interactions between the modules, the derived residuals based on the local models are subject to uncertainties. For this reason, an iterative data-based approach is applied to the residuals to obtain an estimate of their probability density function and detect changes due to occurring faults by the Kullback-Leibler divergence, which has been successfully applied for fault detection tasks, see Youssef et al. (2016). Whereas the investigated sensor layout of the adaptive structure enables the isolation of specified actuator faults within the module, sensor faults are isolated by communicating with the other modules if a change in the Kullback-Leibler divergence is detected. By communicating the detected changes, the fault propagation path is analyzed by the proposed algorithm to isolate the faults.

The main contribution of the paper is an approach for an efficient, modular distributed fault diagnosis using local models of each subsystem suitable for the distributed fault diagnosis of sensor and actuator faults in an adaptive high-rise structure.

The paper is structured in the following way. In section 2, the investigated system is presented and a mathematical formulation of the distributed fault diagnosis problem is given. Section

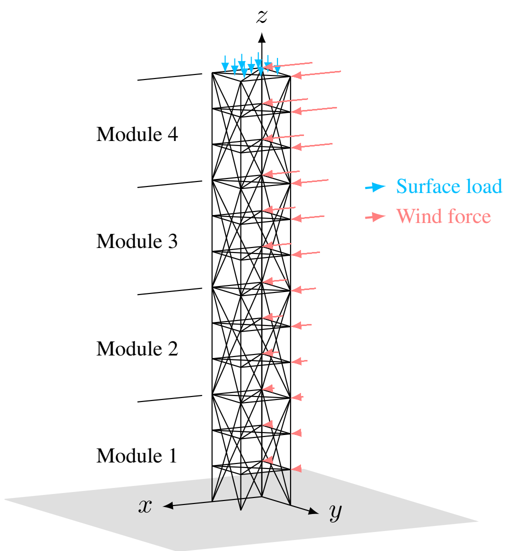

Fig. 2. Investigated high-rise truss structure with four modules and considered disturbances. Modules 1 and 2 are equipped with hydraulic actuators and sensors.

3 presents the modeling of the adaptive structure including the investigated actuator and sensor faults. In section 4, the residual generation and evaluation are discussed and the proposed fault diagnosis algorithm is presented. Afterwards in section 5, the proposed fault diagnosis algorithm is evaluated in a simulation study before in section 6 a brief summary is given.

2. SYSTEM AND PROBLEM DESCRIPTION

In this section, the investigated high-rise adaptive structure as illustrated in figure 2 is introduced and the modular fault diagnosis problem including the assumptions are presented. Furthermore, the challenges due to the interactions of the modules are motivated.

The adaptive structure has a modular design and consists of 4 modules. Module 1 and 2 are equipped with hydraulic actuators and strain gages as well as a computational unit for signal processing and control. Hence, module 1 and 2 are investigated for fault diagnosis based on the local model of the module in this work. The states x of the adaptive structure and its modules are given by the node displacements and velocities in the cartesian coordinate system, the inputs $u = [F_{\mathrm{act},1}, \ldots, F_{\mathrm{act},n_{\mathrm{act}}}]^T$ by the actuator forces $F_{\mathrm{act,i}}$, the outputs y by the strain gage measurements and the unknown disturbances $v = [v_{\mathrm{w}}, \alpha_{\mathrm{w}}, m_i]^T$ are the wind and surface loads depending on the height dependent wind velocity v_{w}, the wind direction α_{w} as well as surface loads on each level $m_i,\ i = 1, \ldots, n_{\mathrm{level}}$. The unknown disturbance influence the system dynamics by the functions $b_v(v)$ and $d_v(v)$ and the resulting state-space model of the structure is given by

$$\begin{aligned} \dot{x} &= \bar{A}x + \bar{B}_u u + \bar{B}_f f_1 + b_v(v), \quad x(0) = \bar{x}_0 \\ y &= \bar{C}x + \bar{D}_u u + \bar{D}_f f_2 + d_v(v). \end{aligned} \tag{1}$$

The state-space model of the adaptive structure, which includes the model of the mechanical structure as well as the impact of the disturbances, is described in Gienger et al. (2020b). The modules state x_{m}, output y_{m} and input u_{m} is a subsystem of the complete system. Consequently, all remaining modules have states $x_{\bar{\mathrm{m}}}$, outputs $y_{\bar{\mathrm{m}}}$ and inputs $u_{\bar{\mathrm{m}}}$ such that the overall

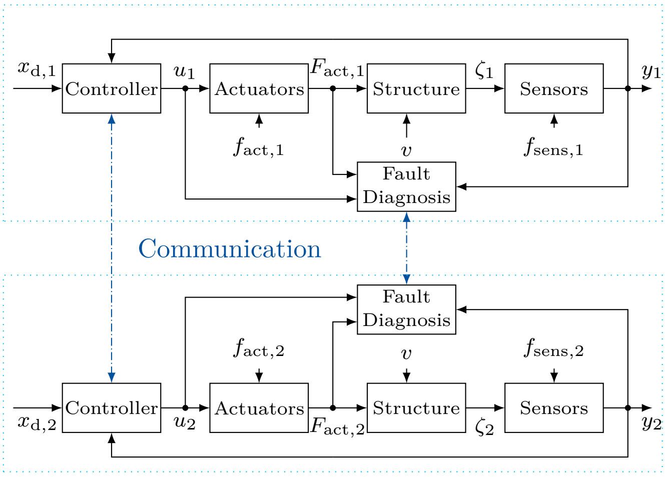

Fig. 3. Control and fault diagnosis structure for two modules.

state-space model of the complete structure is divided into the subsystem of the module and all remaining modules as follows

$$\begin{bmatrix}\dot{x}_{\mathrm{m}}\\ \dot{x}_{\bar{\mathrm{m}}}\end{bmatrix} = \begin{bmatrix}A_{\mathrm{mm}} & A_{\mathrm{m}\bar{\mathrm{m}}}\\ A_{\bar{\mathrm{m}}\mathrm{m}} & A_{\bar{\mathrm{m}}\bar{\mathrm{m}}}\end{bmatrix}\begin{bmatrix}x_{\mathrm{m}}\\ x_{\bar{\mathrm{m}}}\end{bmatrix} + \begin{bmatrix}B_{u,\mathrm{mm}} & B_{u,\mathrm{m}\bar{\mathrm{m}}}\\ B_{u,\bar{\mathrm{m}}\mathrm{m}} & B_{u,\bar{\mathrm{m}}\bar{\mathrm{m}}}\end{bmatrix}\begin{bmatrix}u_{\mathrm{m}}\\ u_{\bar{\mathrm{m}}}\end{bmatrix} + \dots$$
$$\begin{bmatrix}B_{f,\mathrm{mm}} & B_{f,\mathrm{m}\bar{\mathrm{m}}}\\ B_{f,\bar{\mathrm{m}}\mathrm{m}} & B_{f,\bar{\mathrm{m}}\bar{\mathrm{m}}}\end{bmatrix}\begin{bmatrix}f_{\mathrm{m}}\\ f_{\bar{\mathrm{m}}}\end{bmatrix} + \begin{bmatrix}b_{\mathrm{v,m}}(v)\\ b_{\mathrm{v},\bar{\mathrm{m}}}(v)\end{bmatrix}, \tag{2}$$
$$\begin{bmatrix}y_{\mathrm{m}}\\ y_{\bar{\mathrm{m}}}\end{bmatrix} = \begin{bmatrix}C_{\mathrm{mm}} & C_{\mathrm{m}\bar{\mathrm{m}}}\\ C_{\bar{\mathrm{m}}\mathrm{m}} & C_{\bar{\mathrm{m}}\bar{\mathrm{m}}}\end{bmatrix}\begin{bmatrix}x_{\mathrm{m}}\\ x_{\bar{\mathrm{m}}}\end{bmatrix} + \begin{bmatrix}D_{u,\mathrm{mm}} & D_{u,\mathrm{m}\bar{\mathrm{m}}}\\ D_{u,\bar{\mathrm{m}}\mathrm{m}} & D_{u,\bar{\mathrm{m}}\bar{\mathrm{m}}}\end{bmatrix}\begin{bmatrix}u_{\mathrm{m}}\\ u_{\bar{\mathrm{m}}}\end{bmatrix} + \dots$$
$$\begin{bmatrix}D_{f,\mathrm{mm}} & D_{f,\mathrm{m}\bar{\mathrm{m}}}\\ D_{f,\bar{\mathrm{m}}\mathrm{m}} & D_{f,\bar{\mathrm{m}}\bar{\mathrm{m}}}\end{bmatrix}\begin{bmatrix}f_{\mathrm{m}}\\ f_{\bar{\mathrm{m}}}\end{bmatrix} + \begin{bmatrix}d_{\mathrm{v,m}}(v)\\ d_{\mathrm{v},\bar{\mathrm{m}}}(v)\end{bmatrix}. \tag{3}$$

Hence, the state-space model of the module follows as

$$\dot{x}_{\mathrm{m}} = A_{\mathrm{mm}}x_{\mathrm{m}} + B_{u,\mathrm{mm}}u_{\mathrm{m}} + B_{f,\mathrm{mm}}f_{\mathrm{m}} + b_{\mathrm{v,m}}(v) + \dots$$
$$A_{\mathrm{m}\bar{\mathrm{m}}}x_{\bar{\mathrm{m}}} + B_{u,\mathrm{m}\bar{\mathrm{m}}}u_{\bar{\mathrm{m}}} + B_{f,\mathrm{m}\bar{\mathrm{m}}}f_{\bar{\mathrm{m}}}, \tag{4}$$
$$y_{\mathrm{m}} = C_{\mathrm{mm}}x_{\mathrm{m}} + D_{u,\mathrm{mm}}u_{\mathrm{m}} + D_{f,\mathrm{mm}}f_{\mathrm{m}} + d_{\mathrm{v,m}}(v) + \dots$$
$$C_{\mathrm{m}\bar{\mathrm{m}}}x_{\bar{\mathrm{m}}} + D_{u,\mathrm{m}\bar{\mathrm{m}}}u_{\bar{\mathrm{m}}} + D_{f,\mathrm{m}\bar{\mathrm{m}}}f_{\bar{\mathrm{m}}}. \tag{5}$$

The equations illustrate, that the uncertainties for one module are given by the vector $\nu_{\mathrm{m}} = [v^T, x_{\bar{\mathrm{m}}}^T, u_{\bar{\mathrm{m}}}^T, f_{\bar{\mathrm{m}}}^T]^T$ which includes the disturbances, positions and velocities, input forces between the modules and faults.

The control structure with actuator and sensor faults $f_{\mathrm{act},i}$ respectively $f_{\mathrm{sens},i}$ for two modules $i = \{1, 2\}$ is illustrated in figure 3, which allows communication between the fault diagnosis as well as the local controllers with set points $x_{\mathrm{d},i}$.

The proposed fault diagnosis algorithm considering sensor and actuator faults, presented in section 4, is based on the following assumptions:

- The provided force of the actuators are observed, which means that the pressure sensors in the actuators are always healthy
- Actuator and sensor faults do not occur simultaneously
- The faults are detectable and distinguishable from the disturbances in the residual

The observation of the actuator force enables the isolation of actuator faults within the module, but the sensor measurements and faults in one module still depend on the uncertainties ν_{m}. Therefore, communication of the subsystems is necessary for the isolation of the faults.

3. MODELING

This section presents the modeling of the module including the actuator and sensor models with faults. These models are used for residual generation in section 4.

3.1 Mechanical Model of Single Module

The mechanical model of a single module, which is used for the modular fault diagnosis, is derived by finite elements methods yielding the second order differential equation

$$M_{\mathrm{m}}\ddot{\xi}_{\mathrm{m}} + D_{\mathrm{m}}\dot{\xi}_{\mathrm{m}} + K_{\mathrm{m}}\xi_{\mathrm{m}} = F_{\mathrm{u,m}}u_{\mathrm{m}} \tag{6}$$

with initial condition $\dot{\xi}_{\mathrm{m}}(0) = \dot{\xi}_{\mathrm{m},0}$, $\xi_{\mathrm{m}}(0) = \xi_{\mathrm{m},0}$. The variables ξ_{m} are the node displacements of the module in cartesian coordinates, M_{m} is the mass matrix, D_{m} the damping matrix and K_{m} the stiffness matrix of the module. The matrix $F_{\mathrm{u,m}}$ represents the impact of the actuator forces on the module. The influence of the disturbances and couplings to other modules are unknown. The elongations ζ_{m} of the struts in the module, which are measured by the strain gages are given by

$$\zeta_{\mathrm{m}} = L_{\mathrm{m}}\xi_{\mathrm{m}}, \tag{7}$$

where the matrix L_{m} maps the node displacements to the elongation of the struts.

3.2 Actuator Model

The hydraulic actuator model of the adaptive structure is presented in Gienger et al. (2020a) and summarized in the following. For shorter notation, the index i of the actuator will be neglected in the following formulations. The n_{act} actuators in each module transform the signal of the controller to a force on the structure. Herefore, the measurements of the chamber pressures p_{A} and p_{B} are available. The provided force of the actuator is given by

$$F_{\mathrm{act}} = p_{\mathrm{A}}A_{\mathrm{A}} - p_{\mathrm{B}}A_{\mathrm{B}}, \tag{8}$$

where A_{A} and A_{B} are the cross-section areas of the chambers. With this equation, the force is reconstructed and internally controlled by a P-controller towards the desired force u demanded by the controller by adjusting the inlet flows $q_{\mathrm{in,A/B}}$ and outlet flows $q_{\mathrm{out,A/B}}$ by valves. The pressure dynamics in chamber A respectively B are given by

$$\dot{p}_{\mathrm{A/B}} = \frac{\beta}{V_{\mathrm{A/B}}}\left(q_{\mathrm{in,A/B}} - q_{\mathrm{out,A/B}} + q_{\mathrm{il}} + q_{\mathrm{el,A/B}}\right), \tag{9}$$

where β is the compression module of the fluid and $V_{\mathrm{A/B}}$ is the volume of chamber A respectively B, which is assumed to be independent of the displacement of the cylinder and thus $V_{\mathrm{A/B}} = \mathrm{const.}$

The fault scenarios of the actuator considered in this work is internal leackage, external leackage in chamber A respectively B as well as a hard-over failure resulting from a fully opened valve in chamber A. The internal leakage flow between the chambers is described by

$$q_{\mathrm{il}} = k_{\mathrm{il}}\,\mathrm{sign}(p_{\mathrm{A}} - p_{\mathrm{B}})\sqrt{|\frac{2}{\rho}(p_{\mathrm{A}} - p_{\mathrm{B}})|}, \tag{10}$$

where the parameter k_{il} determines the severity of the fault, see e.g. An and Sepehri (2005). The external loss to the environment follows equivalently as

$$q_{\mathrm{el,A/B}} = k_{\mathrm{el,A/B}}\,\mathrm{sign}(p_{\mathrm{A/B}} - p_0)\sqrt{|\frac{2}{\rho}(p_{\mathrm{A/B}} - p_0)|}, \tag{11}$$

where $k_{\mathrm{el,A/B}}$ describes the severity of leaking and p_0 is the ambient pressure.

3.3 Strain gages

Each module is equipped with n_{sens} strain gages, which measure the elongation of the struts. The output equation of the strain gages is given by

$$y_{\mathrm{sg,i}} = k_{\mathrm{sg,i}}(f_{\mathrm{sg},i})\zeta_i + b_{\mathrm{sg},i}(f_{\mathrm{sg},i}) + \epsilon_{\mathrm{sg,i}}, \quad (12)$$

where ζ_i is the elongation of the truss element i, $k_{\mathrm{sg},i}$ is a scaling factor, $b_{\mathrm{sg},i}$ a bias of the sensor and $\epsilon_{\mathrm{sg,i}}$ Gaussian distributed sensor noise $\epsilon_{\mathrm{sg,i}} \approx \mathcal{N}(0, \sigma_{\mathrm{sg}})$ with variance σ_{sg}. The values of the parameters depend on the fault occurring in the sensors and are given as follows.

- **Bias fault:** Parameter $k_{\mathrm{sg,i}} = 1$ and the bias $b_{\mathrm{sg},i} = \mathrm{Unif}(0, b_{\mathrm{sg},i}^{\max})$ is sampled from a uniform distribution with maximum value $b_{\mathrm{sg},i}^{\max}$
- **Random walk:** Parameter $k_{\mathrm{sg,i}} = 1$ and the bias $b_{\mathrm{sg},i}$ is given by a random walk process described by $\dot{b}_{\mathrm{rw}} = \delta_{\mathrm{sg}}$ with $\delta_{\mathrm{sg}} \approx \mathcal{N}(\mu_{\mathrm{sg,rw}}, \sigma_{\mathrm{sg,rw}})$ with mean value $\mu_{\mathrm{sg,r}}$ and variance $\sigma_{\mathrm{sg,rw}}$
- **Zero output:** Parameter $k_{\mathrm{sg,i}} = 0$, $b_{\mathrm{sg},i}(f_{\mathrm{sg},i}) = 0$

4. DISTRIBUTED FAULT DIAGNOSIS

As stated in the problem description, the local models of the single modules do not consider couplings to the other modules such that the measurements of the modules include uncertainties. Moreover, the local models are typically not a precise representation of the real system yielding additional uncertainties in the derived residual. The residuals are determined by the difference in the measured and demanded input forces as well as the deviations between the measurement and model output of each sensor. Since the measurement of the chamber pressures allows the determination of the actuator forces, the considered actuator faults can be isolated within the module. Due to the uncertainties and the stochastic realizations of the faults, the residual is characterized by changes in the Kullback-Leibler divergence determined from the probability density function of each residual. Moreover, the proposed fault diagnosis algorithm communicates the detected changes to other modules to isolate the faults.

4.1 Residual Design

For the distributed fault diagnosis, the model-based residual of each actuator and sensor is generated. The residuals of actuator i at time step k is given by

$$\begin{aligned} r^{\star}_{\mathrm{act},k,i} &= u_{k,i} - F_{\mathrm{act},k,i} \quad (13)\\ &= u_{k,i} - (p_{\mathrm{A},k,i}(f_{\mathrm{act},k,i})A_{\mathrm{A}} - p_{\mathrm{B},k,i}(f_{\mathrm{act},k,i})A_{\mathrm{B}}) \end{aligned}$$

The residual for each sensor i follows from the output equation (12) by neglecting the unknown terms $b_{\mathrm{sg},k,i}(f_{\mathrm{sg},k,i})$ and $\epsilon_{\mathrm{sg,i}}$ such that

$$r^{\star}_{\mathrm{sens},k,i} = y_{\mathrm{sg,k,i}} - k_{\mathrm{sg,k,i}}(f_{\mathrm{sg},k,i})\zeta_{k,i}, \quad (14)$$

where $\zeta_{k,i}$ follows from (7) with (6) by using the observed actuator force as input $u_{\mathrm{m}} = F_{\mathrm{act,m}}$ given by (8). The motivation for this residual selection is that the unknown, high frequency forces on the structure due to wind turbulences are filtered by the system dynamics such that the sensitivity of the wind turbulence on the residual is decreased.

4.2 Residual Evaluation

Due to the system structure and selected sensors, the considered deterministic and stochastic fault realizations are detectable and thus change the stochastic properties of the residual. However, it has to be distinguished between the uncertainties caused by the couplings and faults.
The stochastic properties of a signal are described by its probability density function. For this reason, the residual is based on changes in the probability density function over time, which can be described by the Kullback-Leibler (KL) divergence. The stochastic properties of the residual are determined over a window of length w such that for the actuator and sensor residual follows

$$r_{k,i} = [r^{\star}_{k-w+1,i}, r^{\star}_{k-w+2,i}, \ldots, r^{\star}_{k,i}]^T \in \mathbb{R}^w, \quad (15)$$

where $r^{\star}_{k,i}$ represents the model-based residual of either the actuator $r^{\star}_{\mathrm{act},k,i}$ or sensor $r^{\star}_{\mathrm{sens},k,i}$. For the sake of clarity and shorter notation, the index i of the residual $r_{k,i}$ will be neglected in the following formulations.
To allow an efficient, iterative online adaption of the stochastic properties of the residual, they are approximated as a multivariate Gaussian distribution. The iterative online update of the mean $\bar{r}_k \in \mathbb{R}^w$ and moment matrix $C_k \in \mathbb{R}^{w\times w}$ of the multivariate Gaussian distribution are given by

$$\bar{r}_k = \bar{r}_{k-1} + \frac{r_k - \bar{r}_{k-1}}{k}, \quad (16)$$

$$C_k = C_{k-1} + (r_k - \bar{r}_{k-1})^T(r_k - \bar{r}_k). \quad (17)$$

Hence, it follows for the covariance matrix

$$\Sigma_k = \frac{C_k}{k-1} \in \mathbb{R}^{w\times w}. \quad (18)$$

The KL divergence between the Gaussian distributions $\mathcal{N}_{k-l}(\bar{r}_{k-l}, \Sigma_{k-l})$ of time step $k-l$ and the current distribution $\mathcal{N}_k(\bar{r}_k, \Sigma_k)$ is given by

$$\begin{aligned} D_{\mathrm{KL}}(\mathcal{N}_{k-l} \parallel \mathcal{N}_k) = \frac{1}{2}(&\mathrm{tr}\left(\Sigma_k^{-1}\Sigma_{k-l}\right) + \ldots \quad (19)\\ &+ (\mu_k - \mu_{k-l})^{\mathsf{T}}\Sigma_k^{-1}(\mu_k - \mu_{k-l}) - \ldots\\ &d + \ln\left(\frac{\det \Sigma_k}{\det \Sigma_{k-l}}\right)). \end{aligned}$$

Since the covariance matrix is updated in every time step, the matrix inverse $\Sigma^{-1} \in \mathbb{R}^{w\times w}$ needs to be calculated in each time step as well. This is achieved in a computationally efficient way by the Sherman-Morrison formula for the rank one matrix

$$C_k^{-1} = (C_{k-1} + r_n r_n^T)^{-1} = C_{k-1}^{-1} - \frac{C_{k-1}^{-1} r_n r_n^T A^{-1}}{1 + r_n^T C_{k-1}^{-1} r_n} \quad (20)$$

such that the inverse covariance matrix is given by

$$\Sigma^{-1} = C_{k-1}^{-1} - \frac{C_{k-1}^{-1}(r_k - \bar{r}_{k-1})(r_k - \bar{r}_k)^T C_{k-1}^{-1}}{1 + (r_k - \bar{r}_k)^T C_{k-1}^{-1}(r_k - \bar{r}_{k-1})}. \quad (21)$$

Moreover, the iterative update is also possible for the determinant according to the matrix determinant lemma such that the determinant of the covariance matrix is given by $\det(\Sigma_k) = (1/(k-1))^d \det(C_k)$ and the determinant of the moment matrix by

$$\det(C_k) = \left(1 + (r_k - \bar{r}_{k-1})^T C_{k-1}^{-1}(r_k - \bar{r}_k)\right)\det(C_{k-1}). \quad (22)$$

The deletion of points when considering only data of a specific time interval due to fluctuating disturbances follows equivalently.

4.3 *Distributed Fault Diagnosis Algorithm*

The algorithm for the distributed fault diagnosis in each module under the assumptions in section 2 is summarized in the following:

Input: Residual windows $r_{\mathrm{act},k,i}$ and $r_{\mathrm{sens},k,j}$, detection thresholds $\gamma_{\mathrm{act},i}$ and $\gamma_{\mathrm{sens},j}$ for $i = 1, \dots, n_{\mathrm{act}}$ and $j = 1, \dots, n_{\mathrm{sens}}$

Output: Diagnosed faults $f_{\mathrm{d,act},k,i}$, $i = 1, \dots, n_{\mathrm{act}}$ and $f_{\mathrm{d,sens},k,j}$, $j = 1, \dots, n_{\mathrm{sens}}$

for $i = 1$ to n_{act} **do**
  Iterative update of mean $\bar{r}_{k,i}$, covariance matrix $\Sigma_{k,i}$ and inverse covariance matrix $\Sigma_{k,i}^{-1}$
  Determine KL divergence $D_{\mathrm{KL},i}(\mathcal{N}_{k-l,i} \parallel \mathcal{N}_{k,i})$
  if $D_{\mathrm{KL},i} \geq \gamma_{\mathrm{act,i}}$ or $f_{\mathrm{d,act},k-1,i}$ **then**
    Fault in actuator $f_{\mathrm{d,act},k,i} = 1$
  else
    No fault in actuator $f_{\mathrm{d,act},k,i} = 0$
  end if
end for
for $j = 1$ to n_{sens} **do**
  Iterative update of mean $\bar{r}_{k,j}$, covariance matrix $\Sigma_{k,j}$ and inverse covariance matrix $\Sigma_{k,j}^{-1}$
  Determine KL divergence $D_{\mathrm{KL},j}(\mathcal{N}_{k-l,j} \parallel \mathcal{N}_{k,j})$
  if $f_{\mathrm{d,sens},k-1,j} == 1$ **then**
    Fault in sensor $f_{\mathrm{d,sens},k,j} = 1$
  else
    if $D_{\mathrm{KL},j} \geq \gamma_{\mathrm{sens},j}$ **then**
      Check if actuator fault occurs in module $f_{\mathrm{m,act},k}$
      if $f_{\mathrm{m,act},k} == 1$ **then**
        No fault in sensor $f_{\mathrm{d,sens},k,j} = 0$
      else
        Collect information about actuator fault in other modules $f_{\bar{\mathrm{m}},\mathrm{act},k}$
        if any$(f_{\bar{\mathrm{m}},\mathrm{act},k}) == 1$ **then**
          No fault in sensor $f_{\mathrm{d,sens},k,j} = 0$
        else
          Fault in sensor $f_{\mathrm{d,sens},k,j} = 1$
        end if
      end if
    end if
  end if
end for
return $f_{\mathrm{d,act},k,i}$, $i = 1, \dots, n_{\mathrm{act}}$ and $f_{\mathrm{d,sens},k,j}$, $j = 1, \dots, n_{\mathrm{sens}}$

The inputs of the algorithms are the residual windows of each actuator $r_{\mathrm{act},k,i}$ and sensor $r_{\mathrm{sens},k,j}$ obtained by (15) at every time step as well as the corresponding detection thresholds $\gamma_{\mathrm{act},i}$ respectively $\gamma_{\mathrm{sens},j}$. The thresholds can be derived by the maximum change in the KL-divergence of the nominal system data given by the disturbed but fault-free system operation. The first step in the fault diagnosis algorithm is the iterative update of the mean and covariance matrices for each actuator and the calculation of the KL divergence with the residual windows $r_{\mathrm{act},k,i}$ and $r_{\mathrm{sens},k,j}$. If the KL divergence exceeds a specified threshold $\gamma_{\mathrm{act},i}$, a fault $f_{\mathrm{d,act},k,i}$ in the actuator is detected. Afterwards the same procedure is applied to the different sensors. If the KL divergence of a sensor exceeds the threshold $\gamma_{\mathrm{sens},j}$ a change is detected and needs to be analyzed using the causal paths of the system structure. In a first step, it is ensured that there is no fault in the actuators of the same module. This step is necessary if the controllers of each module communicate or a centralized controller is used for control. Afterwards, the module communicates to check if an actuator fault $f_{\bar{\mathrm{m}},\mathrm{act},k}$ in any other module occurred, which explains the change detected in the sensor.

Table 1. Confusion matrix of 30 simulation scenarios with different actuator and sensor faults.

	$f = 1$	$f = 0$
$f_{\mathrm{P}} = 1$	0.2518	0
$f_{\mathrm{P}} = 0$	0.0122	0.7360

5. SIMULATION STUDY

The effectiveness of the approach is evaluated in a simulation study considering different randomized fault parametrizations as well as random wind and storey loads. For the simulation, a centralized LQR controller and Kalman filter are used to damp the oscillations of the structure. With the centralized controller and observer, the interactions between the modules due to the closed-loop are illustrated. For evaluating the overall performance, 30 fault scenarios are generated using the simulation model in Gienger et al. (2020a) and faults presented in section 3. The confusion matrix of the fault diagnosis results is given in table 1 which is evaluated based on the time samples of each scenario. The presented approach yields accurate prediction results with high true positive and true negative rates as presented in table 1. There are no false positive alarms but a low number of false negative cases, which result from a slightly delayed detection of random walk faults in the strain gages.

Figure 4 illustrates the diagnosis results for a bias fault in strain gage 1 and a random walk fault in strain gage 5 of the first module. Due to the impact of the disturbances which are not included in the residual generation model, the resulting residual deviates from zero. However, these disturbances are identified by the proposed algorithm and the random walk fault occurring at 10.8s triggers the communication to module 2 and the detection of the fault after 0.018s as it can be seen from the peaks in the KL Divergence. The bias fault in the other sensor occurs at 11.1s and triggers the communication immediately, which leads to a correct isolation of the sensor fault. The time trajectories of the leakage fault in chamber A are illustrated in figure 5. The external leakage occurring at 10.8 s is easily detectable from both the derived residuals and the KL divergence. Moreover, the KL divergence of the sensors in both modules is not influenced and communication is not necessary. In contrast, a hard-over failure occurring at 10.8s in actuator 3 of the first module yields to a significant change of the provided force by the actuator and thus affect the measurements of the strain gages of both modules as illustrated in figure 6. The reason for the impact of the actuator fault on the sensor residuals in module 1 is the centralized implementation of the LQR controller and Kalman filter for the simulation study. As it can be seen from the controllers output trajectories in module 1, the actuator fault affects the other controller outputs in the same but also the other module. Because the data-based approach characterizes the uncertainties of the module which also includes the actuator force trajectories of the other module, the KL divergence of the sensors in the other module are affected. However, the proposed algorithm yields an immediate detection of the actuator fault, which is then used to explain the changes in the sensors of both modules based on the communicated actuator fault.

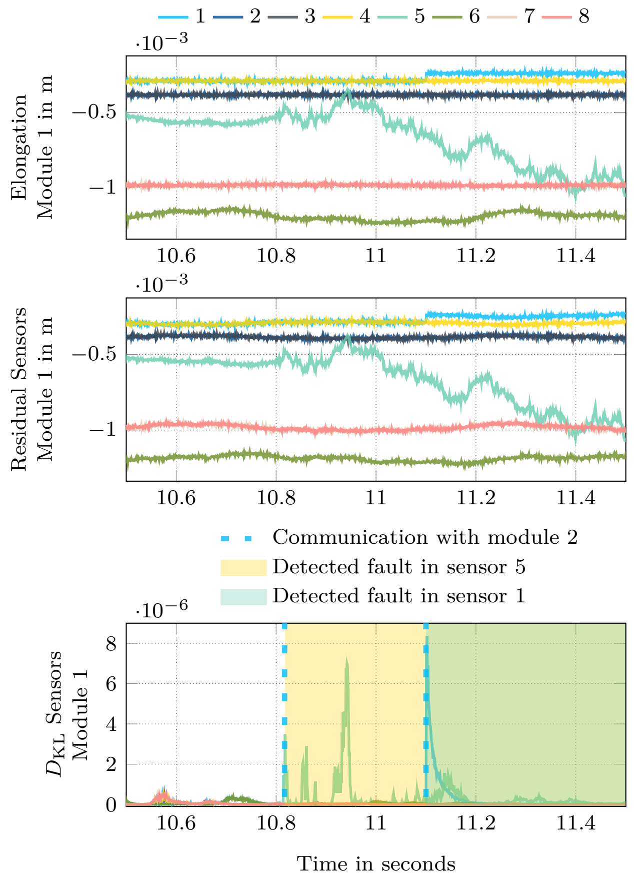

Fig. 4. Measurements of the eight strain gages $1-8$ of module 1 (subfigure 1), corresponding residual (subfigure 2) and KL divergence (subfigure 3) for a random-walk and bias fault in sensors of module 1.

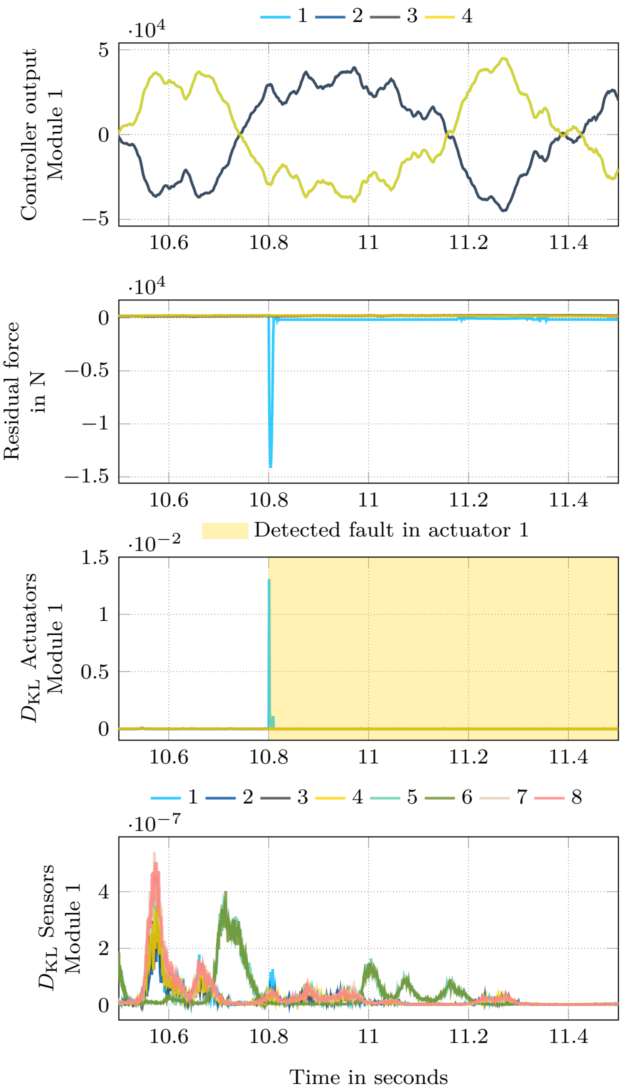

Fig. 5. Controller output of the four actuators $1-4$ of module 1 (subfigure 1), corresponding residual (subfigure 2) and KL Divergence (subfigure 3) as well as KL divergence of sensors $1-8$ (subfigure 4) for an external leackage fault in first actuator of module 1.

6. CONCLUSION

This paper investigated the distributed fault diagnosis in an adaptive high-rise truss structure, which is characterized by a modular design. Based on the local models of the modules, a distributed fault diagnosis scheme is proposed for the diagnosis of actuator and sensor faults in two modules, which are equipped with hydraulic actuators and strain gages. The proposed approach takes into account the uncertainties resulting from the couplings between the modules by approximating the probability density function of their time trajectories as a multivariate Gaussian distribution and detect changes due to faults by the Kullback-Leibler divergence. The available sensors in the investigated adaptive structure and communication of the algorithm enable the isolation of actuator and sensor faults. The effectiveness of the approach was validated for different fault scenarios showing excellent results.

REFERENCES

An, L. and Sepehri, N. (2005). Hydraulic actuator leakage fault detection using extended kalman filter. *International Journal of Fluid Power*, 6(1), 41–51.

Baroni, P., Lamperti, G., Pogliano, P., and Zanella, M. (1999). Diagnosis of large active systems. *Artificial Intelligence*, 110(1), 135–183.

Boem, F., Ferrari, R.M., Parisini, T., and Polycarpou, M.M. (2013). Distributed fault diagnosis for continuous-time nonlinear systems: The input–output case. *Annual Reviews in Control*, 37(1), 163–169.

Daigle, M.J., Koutsoukos, X.D., and Biswas, G. (2007). Distributed diagnosis in formations of mobile robots. *IEEE Transactions on Robotics*, 23(2), 353–369. doi: 10.1109/tro.2007.895081.

Dong, H., Wang, Z., Ding, S.X., and Gao, H. (2014). A survey on distributed filtering and fault detection for sensor networks. *Mathematical Problems in Engineering*, 2014.

Ferrari, R.M.G., Parisini, T., and Polycarpou, M.M. (2012). Distributed fault detection and isolation of large-scale discrete-time nonlinear systems: An adaptive approximation approach. *IEEE Transactions on Automatic Control*, 57(2), 275–290. doi:10.1109/tac.2011.2164734.

Gienger, A., Ostertag, A., Bohm, M., Bertsche, B., Sawodny, O., and Tarin, C. (2020a). Data-based distributed fault diagnosis for adaptive structures using convolutional neural networks. *Unmanned Systems*.

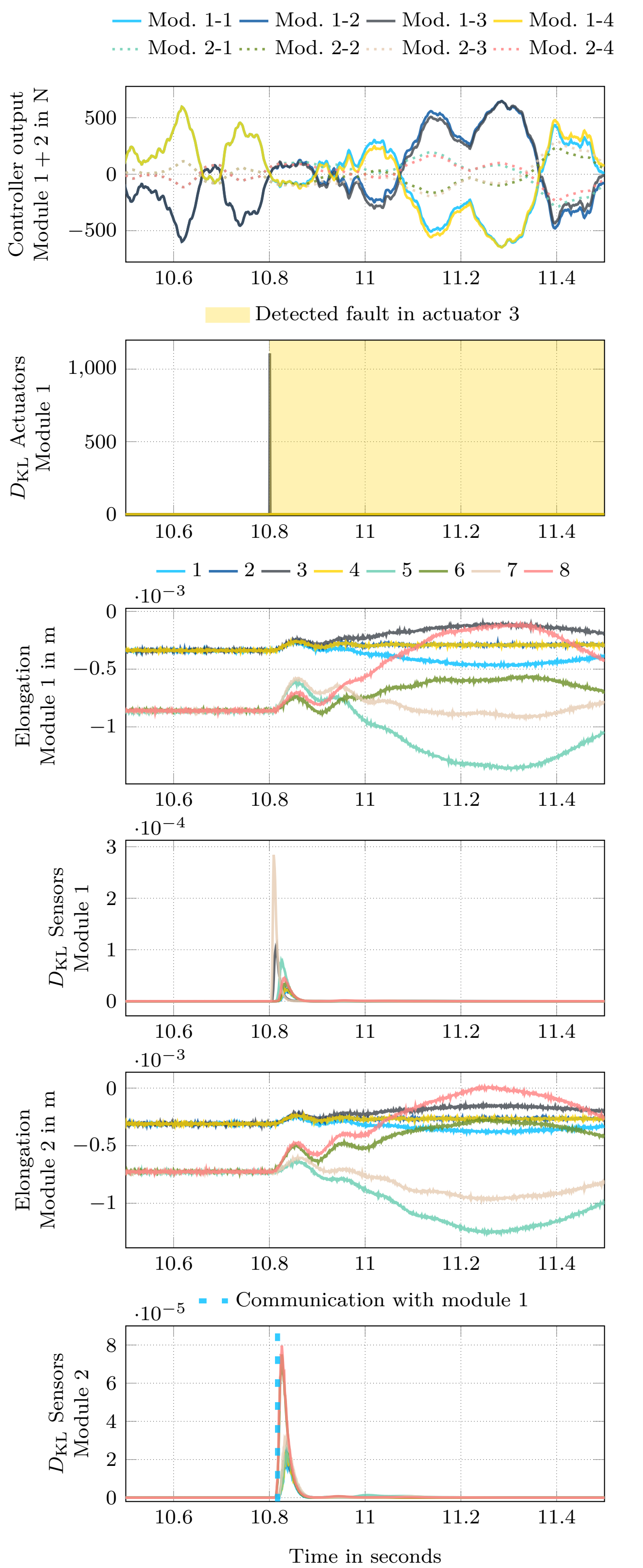

Fig. 6. Controller output of the four actuators $1-4$ of module 1 (solid) and module 2 (dotted) (subfigure 1), corresponding KL divergence (subfigure 2) as well as measurements and KL divergence of sensors $1-8$ of module 1 (subfigure $3+4$) and module 2 (subfigure $5+6$) for a hard-over failure in first actuator of module 1.

Gienger, A., Wagner, J., Böhm, M., Sawodny, O., and Tarín, C. (2020b). Robust fault diagnosis for adaptive structures with unknown stochastic disturbances. *IEEE Transactions on Control Systems Technology*.

Heidingsfeld, M., Kimmerle, U., Tarín, C., and Sawodny, O. (2014). Model-based sensor fault diagnosis for the stuttgart smartshell. In *2014 IEEE International Conference on Automation Science and Engineering (CASE)*, 846–851. IEEE.

Heidingsfeld, M., Rapp, P., Böhm, M., and Sawodny, O. (2017). Gramian-based actuator placement with spillover reduction for active damping of adaptive structures. In *2017 IEEE International Conference on Advanced Intelligent Mechatronics (AIM)*, 904–909. IEEE.

Jiang, Q., Ding, S.X., Wang, Y., and Yan, X. (2017). Data-driven distributed local fault detection for large-scale processes based on the ga-regularized canonical correlation analysis. *IEEE Transactions on Industrial Electronics*, 64(10), 8148–8157.

Korkmaz, S. (2011). A review of active structural control: challenges for engineering informatics. *Computers & Structures*, 89(23-24), 2113–2132.

Li, L., Scaglione, A., and Manton, J.H. (2011). Distributed principal subspace estimation in wireless sensor networks. *IEEE Journal of Selected Topics in Signal Processing*, 5(4), 725–738.

Marelli, D.E. and Fu, M. (2015). Distributed weighted least-squares estimation with fast convergence for large-scale systems. *Automatica*, 51, 27–39. doi: 10.1016/j.automatica.2014.10.077.

OECD (2015). Material resources, productivity and the environment.

Qin, S.J., Valle, S., and Piovoso, M.J. (2001). On unifying multiblock analysis with application to decentralized process monitoring. *Journal of chemometrics*, 15(9), 715–742.

Rapp, P., Heidingsfeld, M., Böhm, M., Sawodny, O., and Tarín, C. (2017). Multimodal sensor fusion of inertial, strain, and distance data for state estimation of adaptive structures using particle filtering. In *2017 IEEE International Conference on Advanced Intelligent Mechatronics (AIM)*, 921–928. IEEE.

Shames, I., Teixeira, A.M.H., Sandberg, H., and Johansson, K.H. (2011). Distributed fault detection for interconnected second-order systems.

Sharifi, R., Kim, Y., and Langari, R. (2010). Sensor fault isolation and detection of smart structures. *Smart Materials and Structures*, 19(10), 105001. doi:10.1088/0964-1726/19/10/105001.

Sobek, W. and Teuffel, P. (2001). Adaptive systems in architecture and structural engineering. In *Smart Structures and Materials 2001: Smart Systems for Bridges, Structures, and Highways*, volume 4330, 36–46. International Society for Optics and Photonics.

Youssef, A., Delpha, C., and Diallo, D. (2016). An optimal fault detection threshold for early detection using kullback–leibler divergence for unknown distribution data. *Signal Processing*, 120, 266–279. doi:10.1016/j.sigpro.2015.09.008.

Zhang, X. and Zhang, Q. (2012). Distributed fault diagnosis in a class of interconnected nonlinear uncertain systems. *International Journal of Control*, 85(11), 1644–1662.