Data-Driven Fault Diagnosis under Sparseness Assumption for LTI Systems

Noom, Jacques; Soloviev, Oleg; Verhaegen, Michel

DOI
10.1016/j.ifacol.2023.10.1176

Publication date
2023

Document Version
Final published version

Published in
IFAC-PapersOnLine

Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 56-2 (2023) 7722–7727

Data-Driven Fault Diagnosis under Sparseness Assumption for LTI Systems

Jacques Noom * **Oleg Soloviev** ** **Michel Verhaegen** *

* *Delft Center for Systems and Control, Delft University of Technology, Mekelweg 2, 2628 CD Delft, The Netherlands (correspondence: j.noom@tudelft.nl)*
** *Flexible Optical BV, Polakweg 10–11, 2288 GG Rijswijk, The Netherlands*

Abstract: Model-based fault diagnosis for dynamical systems is a sophisticated task due to model inaccuracies, measurement noise and many possible fault scenarios. By presenting faults in terms of a dictionary, the latter obstacle is recently addressed using well-known techniques for recovering sparse information (e.g. lasso). However, current state-of-the-art methods still require accurate models and measurements for adequate diagnosis. In our contribution we address the problem of data-driven fault diagnosis in the sense that the model of the linear time-invariant (LTI) system is unknown in addition to the fault. Moreover, our aim is to diagnose (concurrent) faults while only having input/output data and the fault dictionary. This implies the user simply plugs in the data and specifies the set of possible faults in order to know the active faults together with an estimate of the dynamic model. The problem is formulated within a blind system identification context resulting in computationally efficient solutions based on convex optimization.

Keywords: Fault detection and diagnosis; Identification for control.

1. INTRODUCTION

With the developments of Industry 4.0 inducing increased dependence on complex automated systems, it is of crucial importance to recognize abnormalities in early stages of the process. A survey conducted under IFAC Industry Committee members reports the field *fault detection and identification* within the top-three of control technologies with high future impact (Samad et al., 2020). Model-based fault diagnosis methods depend on accurate models, which are not available for complicated industrial processes (Gao et al., 2015a). Likewise, signal-based techniques rely on matching output data with known features (Gao et al., 2015b), which is deficient for timely recognizing faulty behavior in complex systems with varying inputs. Alternatively, there is a vast literature that agrees that knowledge-based fault diagnosis techniques, to be defined in the next paragraph, are the solution to monitoring large-scale industrial systems (Venkatasubramanian et al., 2003; Isermann, 2006; Dai and Gao, 2013; Yin et al., 2014; Ding, 2014; Gao et al., 2015a; Heirung and Mesbah, 2019; Simani, 2021).

Knowledge-based fault diagnosis techniques use large amounts of historical data for extracting features important for discrimination between different operating conditions. For its use of large amounts of data, this group of techniques is often referred to as *data-driven* (Dai and Gao, 2013; Yin et al., 2014; Ding, 2014; Gao et al., 2015a; Simani, 2021). However, these techniques can be effectively partitioned into a (data-based) model acquisition phase (for instance neural network training or parameter estimation in dynamical models) and a model-based fault diagnosis phase. Therefore, the term data-driven implying the absence of a model, may be misleading. Furthermore, knowledge-based techniques generally require labeled data, which can only be acquired when it can be assured the system is in a certain operating condition.

The purpose of this paper is to introduce a true (model-free) data-driven fault diagnosis approach, which only requires input/output data and the fault dictionary in order to diagnose (concurrent) faults in a linear time-invariant (LTI) system. Our data-driven approach does not require historical data of any operating condition acquired at separate time periods prior to conducting diagnosis. It identifies simultaneously a model of the underlying system dynamics plus the active faults. This requires the considered data to be persistently exciting. The particular requirements on the input in relation to the fault dictionary information will be studied in a future extended variant of this paper. For now, we simply assume these requirements are satisfied. The sparseness assumption entails only a small number of faults can be active simultaneously out of a large set of possible faults, which is valid for a large subset of typical fault diagnosis problems.

Our proposed approach is computationally efficient based on convex optimization solutions recently proposed for restricted variants compared to this paper, namely in Zhang (2021) where a full model is assumed to be a priori available, and in Scobee et al. (2015) where fault-free data is assumed. The approach in Chen (2017) deals with a similar problem, however is only devoted to detecting the presence of a fault without selecting the fault at hand from

10.1016/j.ifacol.2023.10.1176

the dictionary. In this contribution, we are also able to diagnose the active faults together with their magnitude.

The manuscript is organized as follows. Sect. 2 presents the methodology, starting with Sect. 2.1 introducing the structured data matrices and Sect. 2.2 recapping the method of Zhang (2021) for model-based fault diagnosis, neglecting the effect of the initial state. This negligence is based on developments in subspace identification (Chiuso, 2007; Verhaegen and Verdult, 2007). The proposed data-driven approach to fault diagnosis is presented in Sect. 2.3. Afterwards, the approach is evaluated in multiple simulation experiments in Sect. 3. Conclusions are drawn in Sect. 4.

2. METHODOLOGY

Consider the observer for a multivariable LTI system (Verhaegen and Verdult, 2007):

$$\begin{aligned} \hat{x}(k+1) &= (A-KC)\hat{x}(k) + Bu(k) + Ky(k) \\ \hat{y}(k) &= C\hat{x}(k) \end{aligned} \tag{1}$$

with estimated state $\hat{x}(k) \in \mathbb{R}^{n_x}$, input $u(k) \in \mathbb{R}^{n_u}$ and estimated output $\hat{y}(k) \in \mathbb{R}^{n_y}$. Using this model, we can write the estimated output $\hat{y}(k)$ as:

$$\begin{aligned} \hat{y}(k) = {} & C(A-KC)^s\hat{x}(k-s) \\ & + \sum_{i=1}^{s} C(A-KC)^{i-1}\Big(Bu(k-i) + Ky(k-i)\Big) \end{aligned} \tag{2}$$

If the system is detectable and K is designed such that $A - KC$ is asymptotically stable, the effect of the state $\hat{x}(k-s)$ decreases to zero for increasing s. This leads to the following approximate Vector Auto-Regressive model with eXogenous input (VARX):

$$\hat{y}(k) \approx \sum_{i=1}^{s} B_i u(k-i) + \sum_{i=1}^{s} K_i y(k-i). \tag{3}$$

The matrices B_i and K_i of compatible size refer to the so-called observer Markov parameters (Phan and Longman, 1996). The VARX model description covers a wide range of multiple-input multiple-output (MIMO) systems and is studied comprehensively in Lütkepohl (2005); Chiuso (2007).

2.1 VARX model identification

To introduce the structured data matrices, we first consider the fault-free identification problem. It should be noted that this step is not required for the execution of the proposed approach introduced later, however essential for building up the relevant knowledge.

Regard the available information

$$\begin{aligned} &[u(k)\ u(k+1)\ \dots\ u(k+N-1)], \\ &[y(k)\ y(k+1)\ \dots\ y(k+N)]. \end{aligned}$$

Then with

$$Y = \begin{bmatrix} y^\top(k+s) \\ y^\top(k+s+1) \\ \vdots \\ y^\top(k+N) \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} B_1^\top \\ B_2^\top \\ \vdots \\ B_s^\top \end{bmatrix}, \quad \mathbf{K} = \begin{bmatrix} K_1^\top \\ K_2^\top \\ \vdots \\ K_s^\top \end{bmatrix}, \tag{4}$$

and the Toeplitz matrices

$$\begin{aligned} T_u &= \begin{bmatrix} u^\top(k+s-1) & u^\top(k+s-2) & \dots & u^\top(k) \\ u^\top(k+s) & u^\top(k+s-1) & \dots & u^\top(k+1) \\ \vdots & \vdots & \ddots & \vdots \\ u^\top(k+N-1) & u^\top(k+N-2) & \dots & u^\top(k+N-s) \end{bmatrix} \\ T_y &= \begin{bmatrix} y^\top(k+s-1) & y^\top(k+s-2) & \dots & y^\top(k) \\ y^\top(k+s) & y^\top(k+s-1) & \dots & y^\top(k+1) \\ \vdots & \vdots & \ddots & \vdots \\ y^\top(k+N-1) & y^\top(k+N-2) & \dots & y^\top(k+N-s) \end{bmatrix} \end{aligned} \tag{5}$$

the following least-squares problem aims at finding the system parameters $\mathbf{B}$ and $\mathbf{K}$ for the 1-step ahead predictor:

$$\min_{\mathbf{B},\mathbf{K}} \left\| Y - [T_u\ T_y] \begin{bmatrix} \mathbf{B} \\ \mathbf{K} \end{bmatrix} \right\|_F^2. \tag{6}$$

The solution to this problem is unique if the matrix $[T_u\ T_y]$ has full column rank. This condition requires the input to be persistently exciting (Verhaegen and Verdult, 2007).

2.2 Model-based fault diagnosis under sparseness assumption

Suppose now that the input term consists of a known element $\mu(k) \in \mathbb{R}^{n_\mu}$ and unknown fault $d(k) \in \mathbb{R}^{n_d}$. Then we can substitute in (1):

$$Bu(k) = \begin{bmatrix} \tilde{B} & F \end{bmatrix} \begin{bmatrix} \mu(k) \\ d(k) \end{bmatrix}. \tag{7}$$

Furthermore, the fault can be modeled as

$$d(k) = \theta(k)z \tag{8}$$

with $\theta(k) \in \mathbb{R}^{n_d \times n_z}$ a dictionary of known fault scenarios (patterns) and $z \in \mathbb{R}^{n_z}$ their corresponding weighing terms. For example, the dictionary $\theta(k)$ can represent sinusoidal, triangular or square waveforms with various frequencies, unit steps with various starting points, or user-defined fault progressions.

As confirmed in Zhang (2021), the diagnosis of additive faults in the framework of (1), (7) and (8) is widely studied (see e.g. Basseville and Nikiforov (1993), Blanke et al. (2006), Ding (2013)), both for time-invariant and time-variant systems with known system matrices A, $\tilde{B}$, C, F and K.

Whereas Zhang (2021) indicates for conventional approaches that "tractable solutions are only available when a small number of possible faults are assumed," recently he proposed a computationally efficient method to diagnose from a large set of possible faults. Neglecting the effects of initial condition (given the fact that $A - KC$ is asymptotically stable (Chiuso, 2007; Verhaegen and Verdult, 2007)) the approach in Zhang (2021) can be (accurately) approximated as follows.

Let $\mathbf{F}$ and $\tilde{\mathbf{B}}$ be constructed from F and $\tilde{B}$ similarly to $\mathbf{B}$ from B in (4). Consider the Kronecker product

$$\mathbf{F}(z) = \mathbf{F} \otimes z \tag{9}$$

and the Toeplitz matrices T_μ and T_θ constructed as T_u in (5) with all elements $u^\top(k)$ replaced respectively by $\mu^\top(k)$ and $\mathrm{vec}(\theta^\top(k))^\top$, such that the VARX approximation becomes

$$Y \approx [T_\mu \ T_\theta \ T_y] \begin{bmatrix} \tilde{\mathbf{B}} \\ \mathbf{F}(z) \\ \mathbf{K} \end{bmatrix}. \tag{10}$$

With the sparseness assumption on z entailing only a small number of faults is active simultaneously, this results in a lasso optimization problem:

$$\min_z \left\| Y - [T_\mu \ T_y] \begin{bmatrix} \tilde{\mathbf{B}} \\ \mathbf{K} \end{bmatrix} - T_\theta \mathbf{F}(z) \right\|_F^2 + \lambda \|z\|_1 \tag{11}$$

with $\mathbf{F}(z)$ given in (9). In words, the output residual is minimized over the fault weighing variables z by subtracting their corresponding fault responses $T_\theta \mathbf{F}(z)$ from the data equation. The 1-norm is included to enhance sparsity on the weighing vector. This approach has shown good performance on both time-invariant and time-variant systems by Zhang (2021), where also the (negligible) effect of the initial condition is taken into consideration. However, this method is sensitive to the provided model parameters which may be erroneous or inaccurate. Furthermore, in some cases the fault has already occurred before the model parameters are identified. This motivates the development of a ('true') data-driven approach to fault diagnosis.

2.3 Data-driven approach to fault diagnosis

In our case of data-driven fault diagnosis the system matrices $\tilde{\mathbf{B}}$, $\mathbf{K}$ and $\mathbf{F}$ are unknown in addition to the fault(s). This implies (11) becomes a bilinear optimization problem, which is computationally expensive due to its nonconvexity. However, from $\mathbf{F}(z)$ it is possible to derive the matrix

$$\mathbf{F}^*(z) = \text{vec}\left(\mathbf{F}^\top\right) z^\top \tag{12}$$

which has rank one (Scobee et al., 2015). Besides, the variable $\mathbf{F}(z)$ has by construction in (9) a degree of sparsity (defined as the ratio of nonzero components) equal to that of z. As a result, the bilinear optimization problem can be replaced by the rank-constrained minimization problem

$$\min_{\tilde{\mathbf{B}}, \mathbf{F}(z), \mathbf{K}} \left\| Y - [T_\mu \ T_\theta \ T_y] \begin{bmatrix} \tilde{\mathbf{B}} \\ \mathbf{F}(z) \\ \mathbf{K} \end{bmatrix} \right\|_F^2 + \lambda \|\mathbf{F}(z)\|_{1,1} \quad \text{s.t. } \text{rank}\big(\mathbf{F}^*(z)\big) = 1. \tag{13}$$

Note that in contrast to (11) where z is the optimization variable, in (13) the quantity $\mathbf{F}(z)$ is an explicit optimization variable. The solution of $\mathbf{F}$ and z can be found up to a multiplicative scalar from singular value decomposition of $\mathbf{F}^*(z)$. Since no model knowledge is assumed, the optimization problem relies on minimizing the output residuals, now with respect to both model parameters as well as fault parameters.

Problem (13) can be relaxed to a convex optimization problem by replacing the rank constraint with an additive weighted nuclear norm to the objective function. The eventual unconstrained convex optimization problem is then

$$\min_{\tilde{\mathbf{B}}, \mathbf{F}(z), \mathbf{K}} \left\| Y - [T_\mu \ T_\theta \ T_y] \begin{bmatrix} \tilde{\mathbf{B}} \\ \mathbf{F}(z) \\ \mathbf{K} \end{bmatrix} \right\|_F^2 + \lambda_1 \left\| \mathbf{F}^*(z) \right\|_* + \lambda_2 \|\mathbf{F}(z)\|_{1,1}. \tag{14}$$

Like optimization problem (6), the solution to $\tilde{\mathbf{B}}$, $\mathbf{F}(z)$ and $\mathbf{K}$ is unique if the matrix $[T_\mu \ T_\theta \ T_y]$ has full column rank. This is now a condition on the persistency of excitation of the joint input $(\mu^\top(k), \text{vec}(\theta^\top(k))^\top)$. However, due to the regularization terms, full column rank of $[T_\mu \ T_\theta \ T_y]$ is not a necessary condition for uniqueness of the solution to (14). Naturally, the problem of model-free data-driven fault diagnosis is not solvable for all types of faults, for example if they are proportional to the input or output. On the other hand, such faults can be diagnosed if they emerge within the considered data window. For this it is required to model possible approximate starting points in the fault dictionary $\theta(k)$. Other fault signatures such as various waveforms or user-defined signals are likely to be identifiable without having the requirement to emerge within the considered data window.

The faults can be isolated using (14) only, however their magnitudes will be biased toward zero due to the additional penalties to the least-squares term. Also, the identified VARX matrices $\tilde{\mathbf{B}}$ and $\mathbf{K}$ may be affected by the bias in $\mathbf{F}(z)$. For refined estimation of the fault magnitudes and system parameters, a second optimization without the 1-norm can be performed over the nonzero elements of $\hat{z}$ found in (14). In practice, this means that the components of the dictionary $\theta(k)$ and the weighing variables z in (7) are in the second optimization neglected according to the 'zero' (in practice below a threshold) elements of $\hat{z}$ found in the first optimization, and in the second optimization $\lambda_2 = 0$.

The choice of the tuning parameters may be nontrivial. However, it can be deduced that a rank one solution is encouraged by increasing λ_1, and the sparsity of z by increasing λ_2. A possible tuning strategy is to set λ_2 to zero first and tune λ_1 such that the predictor performance of (3) (for instance calculated as Variance Accounted For (VAF)) with parameters found in (14) is optimized on a validation data set. While fixing λ_1 to the value found in the first step, λ_2 can be adapted gradually by optimizing the performance of (3) on validation data, with parameters found in (14) after refinement.

3. RESULTS

The simulation results will be presented in three parts. First, the isolation performance of (14) is evaluated under varying conditions. Also the timing results are analyzed in this part. The second part consists of estimating the fault magnitudes and system parameters after reducing bias induced in (14) in the refinement step. The third part compares isolation rates with the model-based approach in (11) based on Zhang (2021) in case of model inaccuracies.

The simulation experiments are performed using an example from Zhang (2021), restricted to a time-invariant system with known inputs except for the faults. The state-space representation is given as

$$\begin{aligned} x(k+1) &= Ax(k) + F\theta(k)z + w(k) \\ y(k) &= Cx(k) + v(k) \end{aligned} \tag{15}$$

detectable with (unknown) system matrices

$$A = \begin{bmatrix} -0.8 & 0.7 & 0.1 \\ -0.6 & 0 & 0.1 \\ 0 & -0.5 & -0.4 \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad F = I_3$$

and $w(k)$ and $v(k)$ zero-mean white noise sequences with covariance I_3 and $0.5I_2$, respectively. The fault dictionary $\theta(k) \in \mathbb{R}^{3\times 50}$ is generated element-wise from a uniform distribution within $[-17.3, 17.3]$, and the fault parameter vector $z \in \mathbb{R}^{50}$ consists of zeros with randomly drawn entries set to one. With a sample size of $N = 100$ and VARX model order $s = 3$, the Toeplitz matrix $T_\theta \in \mathbb{R}^{98\times 450}$ is far from having full column rank. Optimization problem (14) is solved using CVX (Grant and Boyd, 2014). Each simulation experiment is run 100 times for statistical evaluation.

3.1 Fault isolation rates

The rates of successful fault isolation for a varying number of active faults are presented in Fig. 1. The isolation is regarded successful if each nonzero component of $\hat{z}$ satisfying $|\hat{z}| > \epsilon\|\hat{z}\|_\infty$ with $\epsilon = 10^{-2}$ is diagnosed while the other components are not, i.e. no misdetection nor overdetection. For up to four simultaneous faults, the algorithm diagnosed the faults without misdetections nor overdetections, even while many columns of T_θ have linear dependence. For increasing numbers of simultaneous faults, the validity of the sparseness assumption weakens, resulting in decreasing detection performances.

With increasing measurement noise, Fig. 2 shows the performance of the data-driven algorithm in the case of three simultaneous faults. Even in the case of very small signal-to-noise ratios (SNR) around 3 dB, the algorithm is able to diagnose the three faults correctly for a part of the realizations. Furthermore, Fig. 3 shows even in case of low SNR of 3.58 dB, a high performance can be achieved by increasing the number of measurements.

The timing results are shown in Fig. 4 and 5. Optimization (14) is computationally efficient for being convex and unconstrained. The computational time – based on an implementation using CVX version 2.2 in Matlab R2021a on an Intel i7-9750H CPU – appears to increase linearly with respect to the sample size N within the considered domain, however nonlinearly with respect to the VARX model order s. The exact operation count for solving the data-driven fault diagnosis problem will be studied in a future extended variant of this paper.

3.2 Estimation of fault magnitudes and system parameters

As stressed before, the additional penalties in (14) cause a bias in the estimations of $\mathbf{F}(z)$. Hence, a second (refining) optimization similar to (14) but over the elements of $\hat{z}$ determined as nonzero in the first step, and with $\lambda_2 = 0$ is performed in order to refine the estimation of fault magnitudes and system parameters.

Since the data-driven diagnosis problem is originally bilinear, naturally the results $\mathbf{F}$ and z can only be found up to a multiplicative scalar. Therefore, instead of solely analyzing $\hat{z}$, the combined estimated magnitude of $\hat{\mathbf{F}}$ and $\hat{z}$ is verified by comparing the model output $\hat{y}(k)$ with the noise-free system output $Cx(k)$ through the Variance Accounted For (VAF) as defined in Verhaegen and Verdult (2007).

In a single experiment under the latter conditions in Fig. 3 ($N = 220$), optimization problem (14) results in a

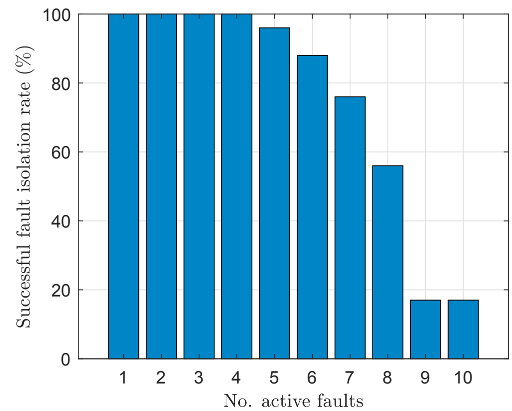

Fig. 1. Successful isolation rate against number of active faults. The results are generated using (14) with $\lambda_1 = 1.5 \times 10^3$ and $\lambda_2 = 2 \times 10^3$.

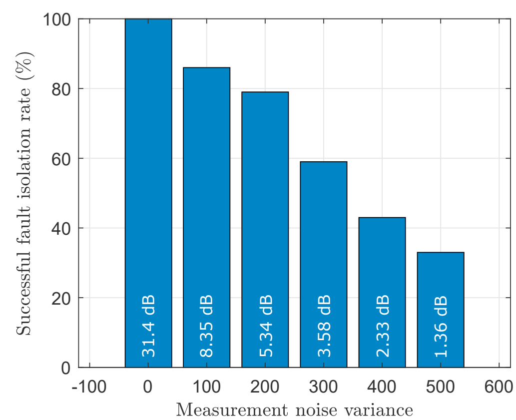

Fig. 2. Successful isolation rate against variance of measurement noise (corresponding average SNRs indicated) in the case of three active faults. The results are generated using (14) with $\lambda_1 = \{2, 2, 5, 5, 7, 10\} \times 10^3$ and $\lambda_2 = \{2, 10, 12, 12, 12, 12\} \times 10^3$ chosen separately for each noise condition.

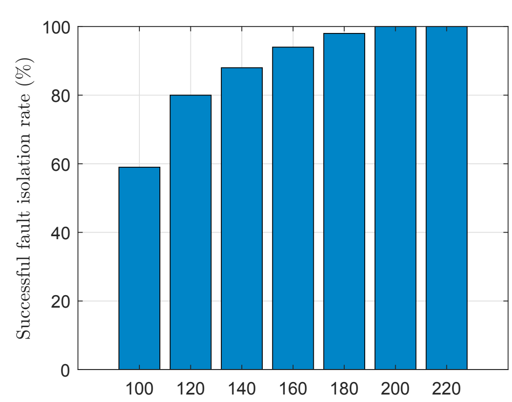

Fig. 3. Successful isolation rate against sample size N in the case of three active faults with SNR 3.58 dB. The results are generated using (14) with $\lambda_1 = \{5, 10, 10, 10, 15, 15, 20\} \times 10^3$ and $\lambda_2 = \{12, 15, 15, 17, 17, 17, 17\} \times 10^3$.

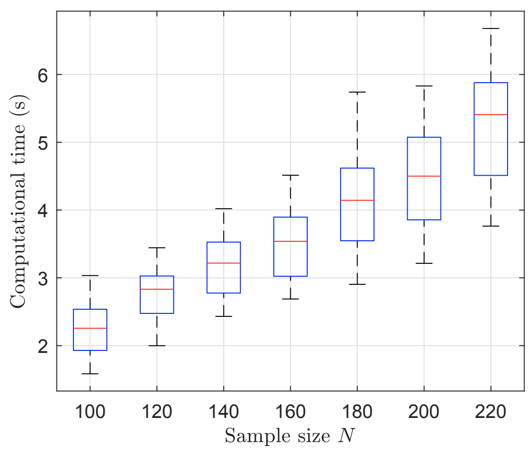

Fig. 4. Timing results of optimization (14) against sample size N corresponding to the experiment in Fig. 3. The computations were performed using Matlab R2021a with CVX version 2.2 on an Intel i7-9750H CPU.

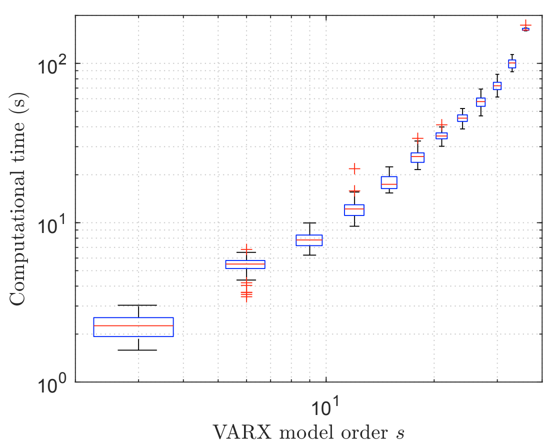

Fig. 5. Timing results of optimization (14) against model order s with sample size $N = 100$.

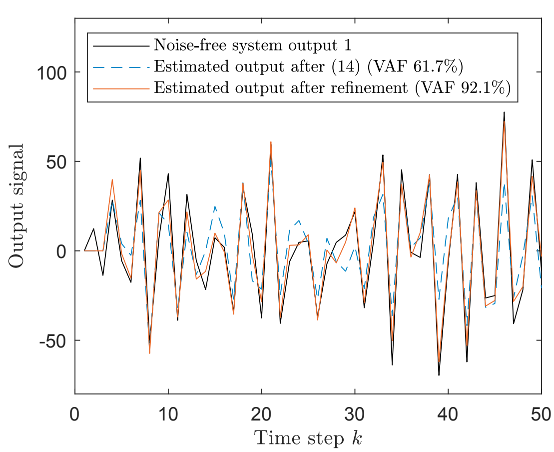

Fig. 6. Noise-free first system output and its estimations after (14) and the refinement in a validation experiment, for a realization of three active faults, SNR 3.58 dB and sample size $N = 220$.

Table 1. Successful isolation rate in case the true system deviates in the left-upper element of A with addition ε. The model-based approach optimizes (11), and the data-driven approach (14).

Model error ε	0.0	1.0	2.0
Model-based (Zhang, 2021)	**100%**	94%	1%
Data-driven (this paper)	**100%**	**100%**	**100%**

VAF on validation data of 61.7% and 65.7% for the two outputs, respectively. The successive refinement results in the VAF being increased to 92.1% and 91.8% for the two outputs, respectively. Fig. 6 presents the corresponding signals belonging to the first system output. It can be confirmed that the refined estimation follows the noise-free system output better and also allows larger signal magnitudes.

From this we can conclude that simultaneously to diagnosing faults, the proposed approach is also able to identify the system parameters. The obtained model parameters can be used afterwards to continue with model-based fault diagnosis and/or to design a suitable controller for reference tracking and disturbance rejection.

3.3 Comparison of data-driven and model-based approach

As mentioned earlier, the proposed data-driven approach in (14) does not require the model parameters in order to diagnose the faults. The model-based approach from Zhang (2021), on the other hand, does require an accurate model. In the following experiment, the performances of both approaches are tested in the case when the true system parameters deviate from the model in (15). The conditions and parameters in (14) are equivalent to those in Fig. 1 in the case of three active faults.

For implementing the model-based approach in (11), the model (15) is approximated by a VARX-model using (2) with K the Kalman gain, and the model order $s = 8$ chosen such that $(A - KC)^p \approx 0$ for all $p \geq s$. The tuning parameter $\lambda = 20 \times 10^3$ is chosen for optimal performance in the case of perfect knowledge of the system parameters.

The results are shown in Table 1. Whereas the performance of the model-based approach degrades for increasing model error, the proposed data-driven approach maintains its accurate diagnostic performance.

4. CONCLUSIONS

This paper introduces a novel model-free data-driven approach to fault diagnosis for which historical data of any operating condition is not required. By providing input/output data and the dictionary of possible additive faults, the approach is able to diagnose the active faults together with the VARX matrices using convex optimization. Simulation results show its diagnosis performance for a varying number of active faults, measurement noise and sample size. The second step of the approach reduces the bias in estimation of fault magnitudes. The resulting diagnosis and system identification can be used for performing model-based fault diagnosis and/or designing a suitable controller for reference tracking and disturbance rejection. The latter is subject for later study.

Further research is planned at extending the presented basic (elementary) solution for LTI systems given in this paper for handling two practically highly relevant conditions. First, it is aimed at handling linear systems for which the parameters vary over time. Second, the data-driven methodology should be extended to the case when active faults (dis-)appear during operation.

REFERENCES

Basseville, M. and Nikiforov, I.V. (1993). *Detection of abrupt changes: theory and application*. Prentice-Hall, Inc., Englewood Cliffs, New Jersey.

Blanke, M., Kinnaert, M., Lunze, J., and Staroswieck, M. (2006). *Diagnosis and Fault-Tolerant Control*. Springer-Verlag Berlin Heidelberg, 2nd edition.

Chen, Z. (2017). *Data-Driven Fault Detection for Industrial Processes*. Springer Fachmedien Wiesbaden.

Chiuso, A. (2007). The role of vector autoregressive modeling in predictor-based subspace identification. *Automatica*, 43(6), 1034–1048.

Dai, X. and Gao, Z. (2013). From model, signal to knowledge: A data-driven perspective of fault detection and diagnosis. *IEEE Transactions on Industrial Informatics*, 9(4), 2226–2238.

Ding, S.X. (2013). *Model-Based Fault Diagnosis Techniques*. Springer-Verlag London, 2nd edition.

Ding, S.X. (2014). *Data-driven design of fault diagnosis and fault-tolerant control systems*. Springer-Verlag London.

Gao, Z., Cecati, C., and Ding, S.X. (2015a). A survey of fault diagnosis and fault-tolerant techniques – Part II: Fault diagnosis with knowledge-based and hybrid/active approaches. *IEEE Transactions on Industrial Electronics*, 62(6), 3768–3774.

Gao, Z., Cecati, C., and Ding, S.X. (2015b). A survey of fault diagnosis and fault-tolerant techniques – Part I: Fault diagnosis with model-based and signal-based approaches. *IEEE Transactions on Industrial Electronics*, 62(6), 3757–3767.

Grant, M. and Boyd, S. (2014). CVX: Matlab software for disciplined convex programming, version 2.1. http://cvxr.com/cvx.

Heirung, T.A.N. and Mesbah, A. (2019). Input design for active fault diagnosis. *Annual Reviews in Control*, 47, 35–50.

Isermann, R. (2006). *Fault-Diagnosis Systems*. Springer-Verlag Berlin Heidelberg.

Lütkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis*. Springer-Verlag Berlin Heidelberg.

Phan, M.Q. and Longman, R.W. (1996). Relationship between state-space and input-output models via observer markov parameters. *WIT Transactions on The Built Environment*, 22, 185–200.

Samad, T., Bauer, M., Bortoff, S., Di Cairano, S., Fagiano, L., Odgaard, P.F., Rhinehart, R.R., Sánchez-Peña, R., Serbezov, A., Ankersen, F., Goupil, P., Grosman, B., Heertjes, M., Mareels, I., and Sosseh, R. (2020). Industry engagement with control research: Perspective and messages. *Annual Reviews in Control*, 49, 1–14.

Scobee, D., Ratliff, L., Dong, R., Ohlsson, H., Verhaegen, M., and Sastry, S.S. (2015). Nuclear norm minimization for blind subspace identification (N2BSID). In *54th IEEE Conference on Decision and Control*, 2127–2132.

Simani, S. (2021). Data-driven methods for fault diagnosis. In V. Puig and S. Simani (eds.), *Diagnosis and Fault-tolerant Control 1: Data-driven and Model-based Fault Diagnosis Techniques*, chapter 5, 131–195. ISTE Ltd and John Wiley & Sons, Inc.

Venkatasubramanian, V., Rengaswamy, R., Kavuri, S.N., and Yin, K. (2003). A review of process fault detection and diagnosis – Part III: Process history based methods. *Computers & Chemical Engineering*, 27(3), 327–346.

Verhaegen, M. and Verdult, V. (2007). *Filtering and System Identification*. Cambridge University Press, Cambridge, UK.

Yin, S., Ding, S.X., Xie, X., and Luo, H. (2014). A review on basic data-driven approaches for industrial process monitoring. *IEEE Transactions on Industrial Electronics*, 61(11), 6418–6428.

Zhang, Q. (2021). Dynamic system fault diagnosis under sparseness assumption. *IEEE Transactions on Signal Processing*, 69, 2499–2508.