Fault Training Matrix for Process Monitoring based on Structured Residuals

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Keywords: Process Monitoring, Model-based Fault Diagnosis, Analytical Redundancy, Complex Systems.

Abstract: Fault Detection and Diagnosis (FDD) approaches have become increasingly important due to the growing demand for reliability and safety for modern systems. During the last decades, many works were reported about FDD approaches, especially model-based ones. The latter relies solely on a developed model that accurately describes the system, without exploiting any additional available data.
In this work, we intent to make use of the physical model as well as historical data, for both normal operating state and faulty states. Hence, the paper focuses on the validation of an experimental approach, called Fault Training Analysis, that analyzes and identifies the causal relations between residuals and faults identified and observed on the system, by dealing with real measurement data from nominal and faulty states. It results on an experimental matrix, called Fault Training Matrix, that enhances the theoretical Fault Signature Matrix.
The effectiveness of the proposed approach is validated through the challenging Tennessee Eastman Process. The application results on a high fault detection rate, a high fault diagnosis rate and a small false alarm rate.

1 INTRODUCTION

To improve systems reliability and ensure a safety production for humans and materials, Fault Detection and Diagnosis (FDD) methods become increasingly important for many technical plants. They are deployed to avoid catastrophic consequences caused by undetected abnormalities and faults.

FDD includes two mains tasks: detection which aims to identify the presence of an eventual fault in the system, and isolation which aims to determine the root causes of the detected fault. Among FDD approaches, one can distinguish between model-based and data-driven categories. Detailed and comprehensive surveys of these latter are given in (Tidriri et al., 2016), (Gao et al., 2015).

Different approaches using mathematical models have been developed in the last years (Liu et al., 2016), (Sidhu et al., 2015), (Tidriri et al., 2018), (Chatti et al., 2016), (Jha et al., 2017). They usually rely on the concept of analytical redundancy to address the fault detection and isolation steps. The basic idea of analytical redundancy consists of comparing the system's actual behavior, provided by real measurements, and the predicted model developed for the system in a normal operating state. Analytical redundancy relations (ARRs) can be generated by using observers, parity space, parameter estimation, graphical approaches, etc (Yang et al., 2015), (Zhong et al., 2015), (Chatti et al., 2014), (Tidriri et al., 2018). The first step consists of the numerical evaluation of the ARRs at every time instant, that generates a set of residuals. Then, these residuals are compared against fixed or adaptive thresholds, computed by using data from normal operating conditions. If there is an inconsistency, the residuals signature vector enables the fault isolation.

However, it is worth noting that the classical approach uses only normal operating data to compute the thresholds, and does not exploit any available faulty data. Nevertheless, modern systems are increasingly automated, allowing the access to a large amount of nominal and faulty data. Therefore, it seems natural to monitor the system using physical models and complete available historical data.

In this work, we intent to make use of all system available information and hence exploit the physical model as well as historical data, whether it belongs to the normal operating state or the faulty states. This is done through an experimental approach, called Fault Training Analysis (FTrA). This latter identifies the causal relations between residuals and faults that already occurred in the system, by dealing with real measurement data. It results on an experimental FSM

Tidriri, K., Chatti, N., Verron, S. and Tiplica, T.
Fault Training Matrix for Process Monitoring based on Structured Residuals.
DOI: 10.5220/0007795600230030
In *Proceedings of the 16th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2019)*, pages 23-30
ISBN: 978-989-758-380-3
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(Fault Signature Matrix) that enhances the theoretical one. This proposed matrix is called FTrM.

Accordingly, the paper is structured as follows. Section 2 will overview the classical model-based fault detection and diagnosis methodology, and point out the main limits and challenges that remain to be addressed. Section 3 will describe the proposed Fault Training Analysis and detail the construction of the associated Fault Training Matrix. In section 4, the application on the well-known Tennessee Eastman Process will show the effectiveness of the proposed approach. Finally, the last section will conclude the paper.

2 MODEL-BASED FAULT DETECTION AND DIAGNOSIS

In this section, the model-based FDD scheme is presented. The limits as well as the challenges are detailed.

2.1 Model-based FDD Scheme

Model-based FDD requires the development of an explicit mathematical model that describes the global behavior of the monitored system (Isermann, 2005), (Ding, 2008), (Tidriri et al., 2016). The model is usually developed based on some fundamental understanding of process physical phenomena. In quantitative models, this understanding is expressed in terms of mathematical functional relationships between the inputs and outputs of the system. Examples of model-based approaches are parity relations, observers, Bond Graphs, etc. (Yang et al., 2015), (Zhong et al., 2015), (Chatti et al., 2014), (Tidriri et al., 2018).

As represented in Figure 1, the first step of a model-based FDD procedure consists of comparing the system's available measurements (measured output) with a priori information represented by the system's mathematical model (predicted output). This is known as Analytical Redundancy Relations (ARRs) generation. These ARRs are specific constraints represented as algebraic differential equations that contain only known variables (measured outputs, system parameters and inputs). The numerical evaluation of the ARRs at every time instant produces a set of residuals r_k, expressed as follows:

$$r_k = \Theta(y_k, u_k, \rho) \tag{1}$$

where k is the time instance, y_k are the measured outputs, u_k the input signals, ρ the system parameters

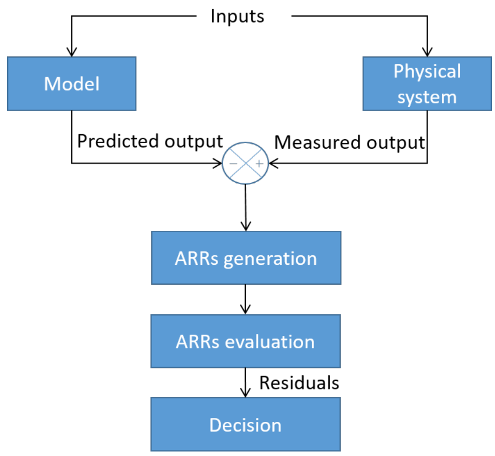

Figure 1: Principle of model-based FDD.

and Θ is a function deduced from the residual generator method chosen for the FDD (observer, parity relations, etc.)

In order to take a decision about the system being in a normal or in a faulty state, the set of residuals are compared, at each time instance k, against fixed or adaptive threshold (See Figure 2). These latter are determined using different methods. One can cite statistical monitoring schemes (such as traditional Shewhart control charts (Areepong, 2013)), or set-based methods that consider the noise effect and model uncertainty (Chatti et al., 2016).

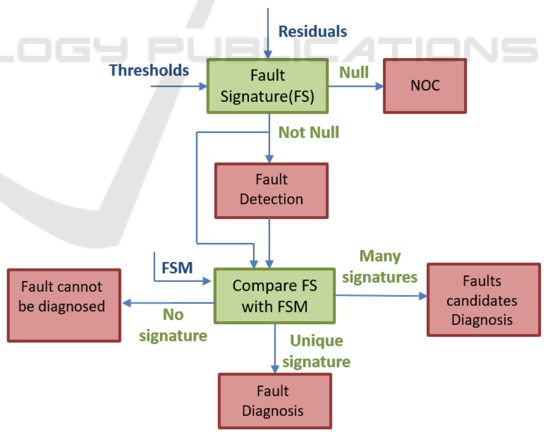

Figure 2: Model-based FDD decision.

The residuals comparison against thresholds produces a set of fault signatures (FS):
$FS(k) = [FS_1(k), FS_1(k), \ldots, FS_n(k)]$ where:

$$FS_i(k) = \begin{cases} 1 & \text{if } r_i \text{ overcomes the associated thresholds} \\ 0 & \text{otherwise} \end{cases}$$

Accordingly, if the FS is null, the system is in Normal Operating Conditions (NOC). Otherwise, an undesired behavior is occurring in the system.

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The fault isolation is then performed by comparing the FS with a specific binary matrix called the Fault Signature Matrix (FSM), which links *theoretically* the residuals sensitivity to the potential faults. The columns of this matrix represent the set of residuals while its rows are related to the faults. The matrix elements are determined as follows:

$$S_{ij} = \begin{cases} 1 & \text{if residual } i \text{ is sensitive to fault } j \\ 0 & \text{otherwise} \end{cases}$$

Hence, when a FS is unique, the fault can be detected and isolated. Otherwise, the obtained FS can lead to an insufficient result, i.e. the fault can be only detected.

2.2 Limits and Challenges

The overview on the model-based diagnosis methodology highlights a number of challenges that may be tackled:

- In order to determine the faults that can be detected and isolated by the model-based method, a theoretical FSM should be built. The classical way for building a FSM considers that all the elements appearing in the residual's expression are associated with faults. Hence, the set of faults that can be detected and isolated is defined solely by the constitutive elements of the generated residuals. This represents a clear limitation since a fault that cannot be expressed in the residual expression cannot be detected and isolated. Therefore, unidentified faults whose origin remains undetermined are not tackled by classical model-based approaches.
- The theoretical FSM links the residuals to the potential faults. These faults must have a physical meaning representing either faults that are associated with components involved in the modeling of the system, or faults on physical phenomena occurring in the process. This reduces the scope of model-based approaches, since the origin of faults can be be explained by other phenomena such as correlations for example.
- Finally, the classical FSM is completely constructed in a theoretical way and does not exploit the historical faulty data that can be available. Only Normal operating data is used to validate the proposed model, and to compute the threshold values.

The purpose of this work is to perform a deeper and an experimental faults-to-residuals correlation study through the exploitation of a physical model as well as historical data, whether it belongs to the normal operating state or the faulty states. Indeed, modern systems are increasingly automated and hence, they allow the access to a significant amount of data.

Therefore, an experimental approach, called Fault Training Analysis (FTrA), is presented in the following. It can determine the causal relations between residuals and faults that already occurred in the system, by dealing with real measurement data, leading to the construction of an experimental FSM that can enhance the theoretical one. Therefore, many challenges aforementioned are raised.

3 FAULT TRAINING ANALYSIS

In this section, the FTrA is detailed and the construction of the FTrM is addressed.

3.1 Fault Training Analysis

First, we assume the following hypothesis:

Hypothesis 1. *A **model** can be developed for the system to be monitored.*

From this available model that describes the system's behavior, a set of residuals $r = [r_1, r_2, ..., r_m]$, generated by applying a model-based FDD approach, is defined.

Second, the following hypothesis are admitted:

Hypothesis 2. ***All sensors** are faults free.*

Hypothesis 3. ***Training data** sets are available.*

Hence, a set of classes $C = \{NOC, D_1, ..., D_n\}$ that represent all the system's states is introduced, where NOC is the normal operating conditions and $D = \{D_1, ..., D_n\}$ is a set of faults that may occur in the system. These faults are identified in the training data sets and can affect the actuators as well as the sensors or the plant.

The idea behind the FTrA is to determine the potential links between the residuals generated on the basis of a model and the faults training data sets available on the system. This can be done through a FTrM, constructed during the training phase.

Definition 1. *A **Fault Training Matrix** is an experimental FSM that evaluates each generated residual with the available faulty training data sets in order to* *link residuals to potential faults, with specific thresholds for each of them. The columns of this matrix represent the set of residuals while its rows are related to the faults identified in the training data sets.*

3.2 Fault Training Matrix

The FTrM construction procedure is given in Figure 3 and detailed as follows:

1. Develop the physical/graphical model describing the system behavior.
2. Generate ARRs.
3. Compute thresholds for each ARR, using historical data from normal operating conditions. This step can be addressed by various approaches as aforementioned.
4. For each fault scenario, use the faulty observations (data) to numerically evaluate each ARR:
   - if the residual overcomes its associated thresholds then it is assumed that the residual is sensitive to the considered fault scenario.
   - if the residual remains between its associated thresholds then it is assumed that the residual is not sensitive to the considered fault scenario.
5. Determine the FTrM elements as follows:

$$T_{ij} = \begin{cases} 1 & \text{if residual } i \text{ is sensitive to fault } j \\ 0 & \text{otherwise} \end{cases}$$

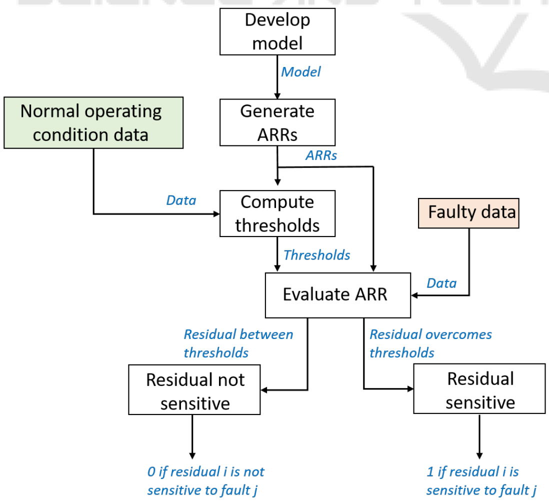

Figure 3: FTrM construction principle.

The FTrM is then used on-line to detect and isolate faults that may occur in the system, following the same reasoning in Figure 2.

4 APPLICATION

In this section, the classical model-based FDD approach as well as the proposed Fault Training Analysis are applied on the well-known Tennessee Eastman Process. A critical discussion and a comparison are given.

4.1 The TEP

The Tennessee Eastman Process (TEP) is a realistic industrial benchmark that consists of five units: a reactor, a condenser, a compressor, a separator and a stripper (Downs and Vogel, 1993). The process flow sheet of the TEP is presented in Figure 4.

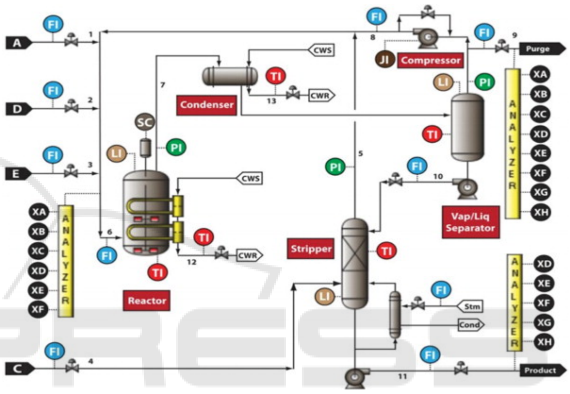

Figure 4: Process flow sheet of the TEP.

The reactants A, D, E, C (corresponding respectively to Streams 1;2;3;4) are introduced into the reactor to form the liquid products G, H and a byproduct F.

It is worth noting that 41 process measurements are available, as well as 12 input variables. More details are given in (Downs and Vogel, 1993).

Many researchers and practitioners evaluated and compared their monitoring approaches on the TEP (Verron et al., 2010), (Atoui et al., 2016), (Ghosh et al., 2011), (Ding et al., 2009), (Yin et al., 2012) since this benchmark can simulate different faults, detailed in Table 1. Indeed, training and test data sets are generated from the TEP by recording the process measurements under NOC and the aforementioned faults.

4.2 Classical Model-based FDD

In this section, a classical model-based approach is applied for the FDD of the TEP. This approach relies on a BG model that has been previously developed by the authors in (Tidriri et al., 2018).

Table 1: Process faults.

Fault	Description	Type
D_1	A/C feed ratio, B composition constant (Stream 4)	step
D_2	B composition, A/C ratio constant (Stream 4)	step
D_3	Condenser cooling water inlet temperature	step
D_4	A feed loss (Stream 1)	step
D_5	C header pressure loss-reduced availability (Stream 4)	step
D_6	A, B, and C feed composition (Stream 4)	random
D_7	Condenser cooling water inlet temperature	random
D_8	Reaction kinetics	drift

The BG model of a part of the TEP (the reactant A) is given as an example in Figure 5.

The BG model of the TEP is then used to generate residuals. This is done by adopting the strategy of eliminating unknown variable by substituting them using only measured and known ones. Details about this procedure can be found in (Chatti et al., 2014), (Tidriri et al., 2018).

18 residuals were generated for the TEP. For the sake of clarity, only 4 residuals expressions, in the steady state, are given in the following:

$$r_1 = y_{A1}F_1 + y_{A5}F_5 + y_{A8}F_8 - C_m\frac{d\mu_{Am}}{dt} - \frac{\mu_{Am}}{R_m} - y_{A6}F_6 \quad (2)$$

$$r_2 = y_{A6}F_6 - C_r\frac{d\mu_{Ar}}{dt} - \frac{\mu_{Ar}}{R_r} + \sum_{j=1}^{3}\nu_{Aj}\tau_j - C_s\frac{d\mu_{As}}{dt} - y_{A8}(F_8+F_9) - x_{A10}F_{10} \quad (3)$$

$$r_3 = y_{B1}F_1 + y_{B5}F_5 + y_{B8}F_8 + y_{B2}F_2 - C_m\frac{d\mu_{Bm}}{dt} - \frac{\mu_{Bm}}{R_m} - y_{B6}F_6 \quad (4)$$

$$r_4 = y_{B6}F_6 - C_r\frac{d\mu_{Br}}{dt} - \frac{\mu_{Br}}{R_r} + \sum_{j=1}^{3}\nu_{bj}\tau_j - C_s\frac{d\mu_{Bs}}{dt} - y_{B8}(F_8+F_9) - x_{B10}F_{10} = 0 \quad (5)$$

The classical model-based approach relies on the fact that residuals expression define the set of detectable and isolable faults. Therefore, according to the expression of residuals r_1 and r_2 related to gas A for example, the detectable faults involve the chemical potentials (μ_{Am}, μ_{Ar}), the sensors which measure several flows (A feed flow F_1, overhead flow from the stripper F_5, recycled flow F_8, reactor feed rate F_6, purge rate F_9, the product separator underflow F_{10}, the reaction kinetics through the reaction rate τ_j, the frictions in the mixing and the reactor zone (R_m, R_r) and the potential energy stored in the mixing, reactor and separator zones (C_m, C_r, C_s).

In order to exploit the available historical data, the FTrA is performed in the following.

4.3 Fault Training Analysis of the TEP

In this step, known variables of the TEP are used in normal operating conditions (NOC) and faulty states, in order to determine which residuals react in presence of different faults. Hence, all obtained residuals are evaluated with available measured outputs and control inputs.

For example, residual r_1 was evaluated using known variables that appear in its expression, namely (F_1, F_5, F_8, F_6) for each faulty scenario $(D_1, D_2, \ldots, D_8)$. If the residual is sensitive to a faulty scenario, its column value in the FTrM will be equal to 1. It appeared that residual r_1 reacts and exceeds its fixed thresholds in presence of measurements from 6 faulty scenarios: $(D_1, D_4, D_5, D_6, D_7, D_8)$. Hence, these faults have an impact on the measured outputs and control inputs within sensors free-fault case. Accordingly, a 1 is added in the FTrM, for each corresponding fault, as shown in Table 2.

The same reasoning is applied for the remaining residuals.

During this testing campaign, we noted that 3 residuals (r_{12}, r_{16}, r_{18}) did not react to any faulty scenario. Therefore, they are not considered in the FTrM.

Furthermore, it appears that it is possible to isolate all faults affecting the TEP using a subset of residuals. Hence, a mutual information based algorithm (Verron et al., 2008) is applied to obtain a reduced subset of 5 residuals with unique FS $(r_6, r_3, r_4, r_1, r_{11})$.
The Fault Signature (FS) is then represented by the following vector of 5 residuals $(r_6, r_3, r_4, r_1, r_{11})$.

The deduced reduced FTrM (Table 3) is used in the on-line monitoring strategy of the TEP, as described previously in Figure 2.

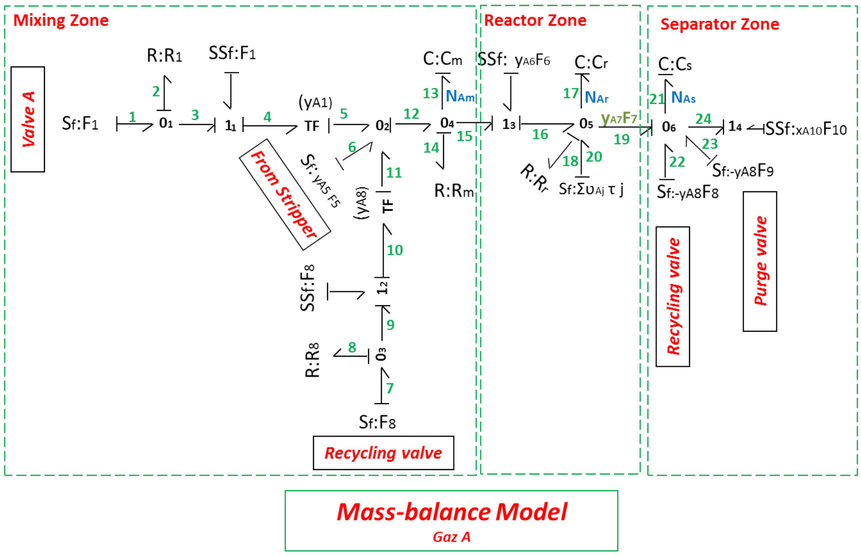

Figure 5: Mass-balance BG of reactant A in the TEP, with derivative causality.

Table 2: Fault Training Matrix (FTrM) linking faults to residuals.

	r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}	r_{11}	r_{13}	r_{14}	r_{16}	r_{17}
D_1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
D_2	0	1	0	1	0	1	0	1	1	0	1	1	1	1	1
D_3	0	0	1	0	0	0	0	0	1	0	1	0	0	0	0
D_4	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0
D_5	1	1	1	0	1	1	0	1	1	1	1	0	0	0	0
D_6	1	0	1	0	0	0	0	0	1	0	1	0	0	0	0
D_7	1	1	0	0	1	1	0	1	1	0	1	0	0	0	0
D_8	1	1	1	1	1	1	1	1	1	0	1	0	0	0	0

Table 3: Reduced Fault Training Matrix (FTrM) linking faults to residuals.

	r_1	r_3	r_4	r_6	r_{11}
D_1	1	1	0	0	0
D_2	0	0	1	1	1
D_3	0	1	0	0	1
D_4	1	0	0	0	1
D_5	1	1	0	1	1
D_6	1	1	0	0	1
D_7	1	0	0	1	1
D_8	1	1	1	1	1

4.4 Results and Comparison

Detection performances are evaluated using the false alarm rate (FAR), which is the percentage of normal samples identified as fault (See (6)), and fault detection rate (FdR), which is the percentage of samples correctly detected (See (7)).

$$FAR = \frac{\text{No. of normal samples identified as fault}}{\text{Total No. of normal samples}} * 100 \tag{6}$$

$$FdR = \frac{\text{No. of faulty samples correctly detected}}{\text{Total No. of faulty samples}} * 100 \tag{7}$$

As for diagnosis performances, they are evaluated using the fault diagnosis rate (FDR):

$$FDR = \frac{\text{No. of samples correctly diagnosed}}{\text{Total No. of samples}} * 100 \tag{8}$$

The results are given in Tables 4 and 5. A comparison between many works reported in the literature (Fisher Discriminant Analysis (FDA) (Yin et al., 2012), Principal Component Analysis (PCA) (Yin et al., 2012), (Ghosh et al., 2014), Partial Least Squares (PLS) (Yin et al., 2012), Dynamic PCA (DPCA) (Yin et al., 2012), Bayesian Network (BN) (Verron, 2007), Independant Component Analysis (ICA) (Yin et al., 2012), Simple Neural Network

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Table 4: Comparison of fault detection performance (%) for the TEP, with reduced FTrM.

	FDA	PCA	PLS	PCA	DPCA	BN	ICA	BG
Average FdR	**79.13**	**90.60**	**90.82**	**90.86**	**92.39**	**98.92**	**98.95**	**99.94**
FAR	**3.11**	**6.13**	**10**	**1.56**	**10.13**	**1.13**	**2.75**	**0.38**

Table 5: Comparison of fault diagnosis performance (%) for the TEP, with reduced FTrM.

	SNN	SVM	PCA	NN	BN	BG
Average FDR	**60.63**	**62.77**	**74.82**	**79.13**	**95.78**	**88.66**

(SNN) (Eslamloueyan, 2011), Support Vector Machine (SVM) (Jing and Hou, 2015), PCA (Jing and Hou, 2015), NN (Eslamloueyan, 2011), BN (Verron, 2007)), based solely on data, and the proposed enhanced BG approach is addressed.

The absence of model-based approaches within this comparison is due to the fact that no work has attempted to detect and diagnose the faults affecting the TEP by using a model. The red color indicates the best result.

According to Table 4, it appears that the proposed BG approach presents the best detection performances. Indeed, it has the highest FdR (99.94%). 6 faults are perfectly detected ($D_1, D_2, D_4, D_5, D_7, D_8$) in 100% of the observations. Furthermore, the BG approach shows the lowest FAR (0.38%).

Thus, the proposed BG approach shows the best FAR and FdR.

Regarding the diagnosis performances, the proposed BG approach shows the second best performance, with an average FDR of 88.66%, as indicated in Table 4.

Accordingly, the BG approach, enhanced with the FTrA, presents better or comparable performances than many data-driven methods reported in the literature.

5 CONCLUSION

In this work, an enhanced model-based approach was proposed for fault detection and diagnosis of a well-known industrial benchmark: the Tennessee Eastman process.

The proposed approach improves the classical fault detection and diagnosis model-based scheme by extending it to an experimental approach, i.e. the Fault Training Analysis, that exploits the available historical data from nominal as well as faulty states. The purpose of this latter is to identify the causal relationships between residuals and faults. The fault training analysis results on an experimental matrix, called Fault Training Matrix, that enhances the theoretical Fault Signature Matrix.

The proposed approach was validated through the Tennessee Eastman Process, and shows a high fault detection rate, a high fault diagnosis rate and a small false alarm rate.

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