

On improving fault detection and diagnosis using alarm-range normalisation ^{*}

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Abstract: Alarm systems based on engineering and safety considerations are the prime source of information for operators when it comes to abnormal situations. Conversely, the presence of fault detection and diagnosis algorithms in process plants is still limited, in comparison with other process control technologies. This work presents a simple way to integrate the information contained in the alarm systems into the fault detection and diagnosis algorithm. A normalisation of the process measurements based on the alarm thresholds is proposed, improving the robustness of the algorithm with regard to the variability of the measurements across fault occurrences in industrial systems.

Keywords: Alarm systems, Fault detection and diagnosis, Alarm flood analysis.

1. INTRODUCTION

Alarm management and Fault Detection and Diagnosis (FDD) are two disciplines that are closely related but still separated in the industry. Alarm management corresponds to a collection of processes and practices for determining, documenting, designing, operating, monitoring, and maintaining alarm systems (IEC, 2014). It belongs to the sphere of process safety with established practices and standards (IEC, 2014). By contrast, FDD has emerged from the process control community as a support tool for abnormal situation management but it has a limited application in the industry compared to other process control technologies (Shu et al., 2016). Fault detection consists in determining whether a fault happened and fault diagnosis consists in determining which fault happened through fault isolation (i.e. finding the variables affected by the fault) or fault identification (i.e. identifying the type of fault that occurred). Numerous classification approaches to fault detection and fault identification have been proposed but Ming and Zhao (2017) have highlighted that applications in industrial systems are still scarce in the literature because historical data requirements and variability of real processes make it hard to make the leap from a simulated system to an industrial case. The integration of alarm management and FDD can help in that regard.

Researchers have proposed multiple ways to integrate the two paradigms. Most works have been focussed on improv-

ing alarm management using statistical process control tools on process measurements (Wang et al., 2016). Alarm design based on process measurements is an active area of research. Several methods have been proposed to design the best alarm thresholds based on process measurements using univariate considerations (Xu et al., 2012) or multivariate considerations (Yang and Guo, 2017). Alarm chattering, alarm configuration and alarms triggered by abnormality propagation are other problems for which solutions based on the analysis of process measurements have been proposed (Wang et al., 2016).

Some works have proposed FDD approaches solely based on alarm data. Pattern matching of alarm floods is one of those approaches (Yang and Guo, 2017). Initially designed for alarm reduction by offline analysis of alarm sequences (Cheng et al., 2013), the algorithms have been extended online to provide support to the operators through identification of the ongoing alarm floods (Lai et al., 2017; Lucke et al., 2018). Alarm prediction (Zhu et al., 2016) and root cause diagnosis based on alarms (Yu et al., 2015) have also been proposed.

However, very few works have investigated the opportunities to improve FDD by combining process measurements with information from the alarm system. Rodrigo et al. (2016) and Hu et al. (2017) demonstrate the benefits of a preliminary alarm data analysis for root cause diagnosis. Online fault detection and identification combining process measurements with alarms is still an open question.

The present work suggests a way to take into account information from the alarm system in the preprocessing of the process measurements used for FDD in order to make the algorithms more robust, and thus more applicable to the

^{*} Financial support is gratefully acknowledged from the Marie Skłodowska Curie Horizon 2020 EID-ITN project PROcess NeTwork Optimization for efficient and sustainable operation of Europe's process industries taking machinery condition and process performance into account PRONTO, Grant agreement No 675215.

industry. It is common practice to use statistical normalisation for fault detection and identification in industrial processes (Russell et al., 2000). This paper proposes a normalisation based on the alarm thresholds as an alternative and demonstrates the advantages of that approach. The aim of the new normalisation method is to place the variations of the process measurements in the context of the safe operational range defined during the alarm design stage based on engineering and safety considerations. The weight (as defined in Section 2.3) of the noisy variations in the classification algorithm is reduced compared to the weight of the variations that are significant with regard to the alarm thresholds. The new normalisation approach is tested on an industrial case study and compared to the traditional normalisation approaches using a benchmark algorithm for fault detection and fault identification.

Section 2 develops the concept of integrating the alarm thresholds in the FDD approach and details the experiment chosen to validate the concept. Section 3 presents the results of the normalisation approaches chosen for fault detection and fault identification on a gas separation plant. Section 4 contains interpretations of the results and Section 5 provides concluding remarks.

2. FAULT DETECTION AND DIAGNOSIS USING ALARM-RANGE NORMALISATION

2.1 Alarm systems and fault detection and diagnosis

An alarm is an audible or visible means of indicating to the operator an equipment malfunction, process deviation, or abnormal condition requiring a timely response (IEC, 2014). Several types of alarms and events exist on a plant but this work considers only absolute alarms, i.e. alarm generated when an alarm threshold is exceeded (IEC, 2014). The alarm thresholds are designed during the engineering stage of the plant based on safety and technical considerations according to the alarm response timeline in Figure 1. The consequence threshold is first defined as the limit after which a consequence begins to occur (e.g. for the level of a tank, it could be the maximum level the tank can admit before overflow). The alarm threshold is defined from the consequence threshold taking into

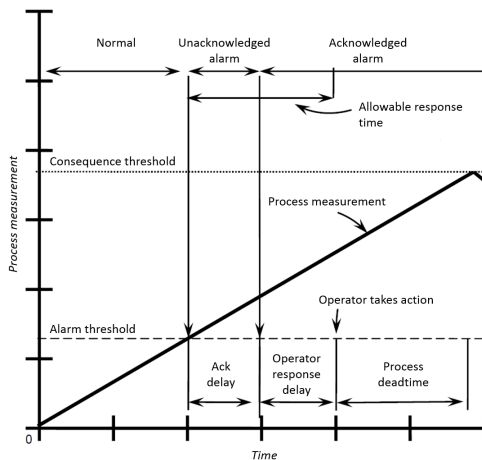


Fig. 1. Alarm response timeline reproduced from IEC (2014).

account the process deadtime, the operator response delay and the acknowledgement delay for the corresponding process measurement. A high and a low alarm threshold are usually defined for each process variable.

Alarms are the foremost indicators for operators when it comes to detecting and identifying ongoing abnormal situations on the plant, as the information is condensed according to ergonomic considerations. In some cases, e.g. alarm floods (condition during which the alarm rate is greater than the operator can effectively manage (IEC, 2014)), additional processing of the alarm sequences is useful to identify the ongoing faults as proposed by Lai et al. (2017) and Lucke et al. (2018). However, the case study presented by Lucke et al. (2018) highlights the limitations of a fault identification system based on alarms only. Firstly, different types of abnormal situations can be difficult to distinguish based on the limited number of alarms triggered. Secondly, reliable identification of the ongoing situation can generally be provided only after two thirds of the alarm sequence has been triggered, which can be several minutes after the first symptoms appear in the process measurements.

Therefore, taking process measurements into account for FDD systems is recommended to improve the accuracy and reduce the time delay required for the identification. Nevertheless, the integration of alarm systems in the FDD framework is beneficial in two ways. Firstly, alarm logs can help isolating and labelling abnormal situations from historical data during the data preparation stage (using e.g. alarm floods or trip events to detect partial or total plant shutdowns). Additionally, as will be shown in the next section, alarm thresholds can be used to normalise the process measurements to improve the robustness of the algorithm with regard to the variability of those measurements.

2.2 Normalisation of process measurements

The preprocessing of the process measurements has a great influence on the results of the FDD algorithms, and normalisation is the first step. The most common normalisation approaches in the FDD literature are mean-centering and standardisation.

Mean-centering Nearly all approaches used in FDD assume the data samples have zero means. Mean-centering is usually straightforward, except in the case of multimode and time-varying process monitoring, which is out of the scope of this paper.

Standardisation The common practice in FDD is to auto-scale the variables to zero mean and unit variance, especially since it involves heterogeneous quantities. For a time series X defined as a sequence of measurements $\{x_1, x_2, \dots, x_n\}$, the standardised measurements can be expressed as:

$$\tilde{x}_i = \frac{x_i - \mu}{\sigma} \quad (1)$$

where \tilde{x}_i is the standardised process measurement, x_i the raw process measurement, μ the mean and σ the standard deviation of the time series X . The computation of the statistical indicators μ and σ depends on the application. The most common approach is to compute μ and σ on

Table 1. Normalisation approaches selected.

Mean-centering	$\tilde{x}_i = x_i - \mu$
N standardisation	$\tilde{x}_i = \frac{x_i - \mu}{\sigma_n}$
NF standardisation	$\tilde{x}_i = \frac{x_i - \mu}{\sigma_{nf}}$
AR normalisation	$\tilde{x}_i = \frac{x_i - \mu}{a_H - a_L}$

the normal operation data used for training the model. Those values can be used to standardise both the faulty data used for training (if needed in the model) and the test data. In order to obtain a better weighting of the variables for the fault identification, an alternative is to compute the standard deviation on the whole training data used for the model, that is both normal and faulty data.

Alarm-range normalisation The thesis of this work is to use the absolute alarm thresholds of the selected process measurements as a reference for the normalisation. The distance between the high threshold a_H and the low threshold a_L can be used as an alternative to the standard deviation to characterise the variability of the process measurements.

The four normalisation approaches considered in the following are summarized in Table 1. The mean-centering approach keeps the amplitude of the original process measurements. The alarm range (AR) normalisation uses the difference between the high alarm threshold a_H and the low alarm threshold a_L . The Normal (N) standardisation uses the standard deviation computed on a normal historical data σ_n while the Normal Faulty (NF) standardisation uses the standard deviation computed on normal and faulty historical data σ_{nf} . All four normalisations use the mean μ computed on normal data.

2.3 Benchmark algorithm

The proposed AR normalisation and the three other normalisations listed in Table 1 are tested on a fault detection and fault identification problem using a popular method for FDD in the industry (Vargas et al., 2017), the 1-nearest neighbour (1NN) classification algorithm which associates each point with the closest point in the feature space (Fix and Hodges, 1951). Each feature vector Y_i at a sample time i corresponds to a plant profile, i.e. to the values of the M selected normalised process measurements at the sample time i :

$$Y_i = [\tilde{x}_{i,1} \ \tilde{x}_{i,2} \ \dots \ \tilde{x}_{i,M}]' \quad (2)$$

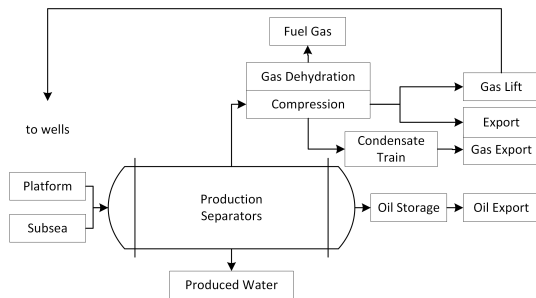


Fig. 2. Process overview of the separation plant.

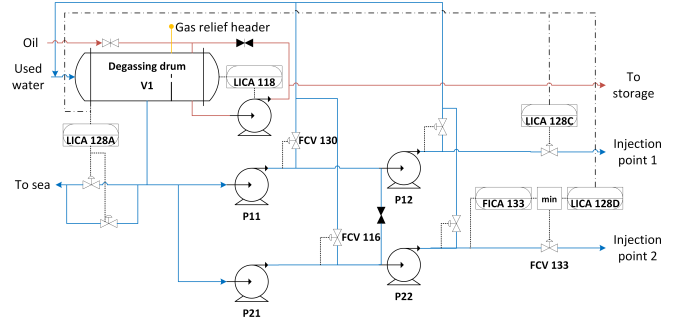


Fig. 3. Process diagram of the PWRI section. Blue indicates the water system, brown the oil system, and yellow the gas system.

Several occurrences of the same type of abnormal situation can be grouped together as a class, where each occurrence O is defined as a set of consecutive feature vectors between the start time t_s and the end time t_e of the abnormal situation:

$$O = \{Y_{t_s}, Y_{t_s+1}, \dots, Y_{t_e}\} \quad (3)$$

The training set \mathcal{T} of the algorithm of Vargas et al. (2017) contains the feature vectors of one occurrence of each class of abnormal situation and of one occurrence of the normal class (corresponding to a normal operation period). During the online fault detection and identification, each new feature vector Y_t is compared to all the feature vectors Y in the training set \mathcal{T} using a Euclidian distance, and the nearest neighbour Y_{NN} is chosen such as:

$$d(Y_t, Y_{NN}) = \min_{Y \in \mathcal{T}} d(Y_t, Y) \quad (4)$$

where the distance d between two feature vectors Y_1 and Y_2 is defined as:

$$d(Y_1, Y_2) = \sqrt{\sum_{i=1}^M (\tilde{x}_{1,i} - \tilde{x}_{2,i})^2} \quad (5)$$

A fault is detected if the nearest neighbour does not belong to the normal class, and the identified fault corresponds to the class of the nearest neighbour. The *weight* of a process measurement k in the classification outcome is defined by the distance $(\tilde{x}_{1,k} - \tilde{x}_{2,k})^2$, which depends on the amplitude of the variations in the process measurement k .

An alternative implementation of the algorithm is also tested in the case study, where each feature vector Y_i at a sample time i corresponds to stacked consecutive plant profiles of the last K sample times (Vargas et al., 2017) in order to introduce information about the development of the fault in the classifier:

$$Y_i = [\tilde{x}_{i-K+1,1} \ \dots \ \tilde{x}_{i-K+1,M} \ \dots \ \tilde{x}_{i-1,1} \ \dots \ \tilde{x}_{i-1,M} \ \tilde{x}_{i,1} \ \dots \ \tilde{x}_{i,M}]' \quad (6)$$

Table 2. Abnormal situation classes.

Class	Description	Number of occurrences
1	Low suction pressure without pump trip	2
2	Low suction pressure with pump trip	3
3	Pump trip due to fuel change	8
4	Pump trip due to vibrations	2
5	Pump trip due to burner temperature	3

Table 3. False detection rate.

False detection rate (%)	One plant profile	Two plant profiles
Mean-centering	18.8	0.0
N standardisation	3.4	0.0
NF standardisation	2.3	0.0
AR normalisation	1.6	0.0

3. INDUSTRIAL CASE STUDY

3.1 Description of the industrial case study

The industrial case study is an offshore gas oil separation plant, designed to separate crude oil, gas and condensates next to the well before export. An overview of the process is given in Figure 2. The study focusses on the Produced Water Reinjection (PRWI) section represented in Figure 2. Recurrent abnormal situations have been detected in this section over a period of four months. Five different types of abnormal situations have been identified based on analysis of the alarm logs. Each type of abnormal event is associated with different root causes (see Table 2):

- Classes 1 and 2 corresponds to abnormal situations that are triggered by a low suction pressure (or suction flow) in the water system. The deviations in pressure and flow lead to an alarm flood. While the situation can be automatically handled and goes back to normal after a few samples in class 1, the low values trigger a trip of pump P21 in events of class 2 eventually leading to an overflow of the degassing drum.
- Abnormal situations of class 3 correspond to a fuel change in the PWRI section from diesel to gas (or vice versa), making P11 or P21 (or both) trip, possibly repeatedly, and leading the pressure and flow to go low in the system, triggering an alarm flood.
- Abnormal situations of class 4 correspond to trips of P21 due to high vibrations as the HH alarm in the vibration probe of the pump motor triggers.
- Abnormal situations of class 5 correspond to a trip of P22 due to a deviation in the exhaust burner temperature.

3.2 Detection and identification of the abnormal situations

The five classes of abnormal situations cover the same area of the plant and have similar consequences, e.g. drop in the pressures and flows of the water system and possibly overflow of the degassing drum. For this reason, they all trigger alarm floods. Focussing on classes 2 and 3 as the two of the most recurrent alarm floods on the plant in the long run, Lucke et al. (2018) showed that events from those classes were not perfectly distinguishable using algorithms based on alarm sequences only. When distinguishable, a reliable diagnosis could only be provided late in the sequence, typically after two thirds of the alarm flood sequence has appeared. Using process measurements is a means to capture the information contained in the process measurement prior to the alarm occurrence, and therefore to focus on the causes of the abnormal situations and not only on their consequences. In that regard, it allows earlier identification and improves the accuracy of the identification.

The study is carried out on the 33 process measurements included in the two areas covering the PWRI section (constantly null process measurements are removed beforehand). The sampling period is 9 seconds. Alarms and events are extracted from the safety system, and abnormal episodes are initially located from the analysis of the alarm and event logs. The alarm thresholds are extracted from the engineering files of the plant. The model is trained on one occurrence of each class of abnormal episode, which amounts to five to seven observations per class. One normal episode of the same length is also used for training for the normal class. The other occurrences are kept for testing.

The four types of normalisation listed in Table 1 are studied. As several normal operation modes exist, the mean value of the current normal operating regime is used instead of a single mean value computed on a normal operation period. The mean μ is computed as the mean over a set of normal points a few minutes before the fault occurs. Transition stages between operation regimes are not in the scope of this work. In addition, a minimum cut-off value of 1.0 is set for σ_n and σ_{nf} .

Fault detection The false detection rates of the algorithms are tested on a normal operation period of the

Table 4. Confusion matrices with one plant profile per feature vector (top table) and two plant profiles per feature vector (bottom table).

Class	Mean-centering						N standardisation						NF standardisation						AR normalisation					
	1	2	3	4	5	MD	1	2	3	4	5	MD	1	2	3	4	5	MD	1	2	3	4	5	MD
1	6	0	0	0	1	0	7	0	0	0	0	0	7	0	0	0	0	0	7	0	0	0	0	0
2	0	12	0	2	0	0	0	2	0	12	0	0	0	12	0	2	0	0	0	12	0	0	0	2
3	0	3	38	1	0	1	4	10	27	2	0	0	0	3	38	1	0	1	0	0	41	0	0	2
4	0	0	0	6	0	1	0	0	0	6	1	0	0	0	0	5	1	1	0	0	0	5	1	1
5	0	0	0	1	10	0	1	0	0	2	8	0	0	0	0	3	8	0	0	0	0	2	8	1

Class	Mean-centering						N standardisation						NF standardisation						AR normalisation					
	1	2	3	4	5	MD	1	2	3	4	5	MD	1	2	3	4	5	MD	1	2	3	4	5	MD
1	6	0	0	0	1	0	6	0	0	0	0	1	6	0	0	0	0	1	6	0	0	0	0	1
2	0	11	0	1	0	2	0	0	0	12	0	2	0	11	0	1	0	2	0	11	0	0	0	3
3	0	4	32	0	0	7	3	15	21	0	2	2	0	4	33	0	3	3	0	0	37	0	0	6
4	0	0	0	5	0	2	0	0	0	5	1	1	0	0	0	5	1	1	0	0	0	5	1	1
5	0	0	0	0	10	1	1	0	0	0	9	1	0	0	0	0	9	2	0	0	0	0	9	2



Fig. 4. Training plant profiles of class 2 (yellow points) and class 4 (blue points) and test plant profiles of abnormal situation A of class 2. The green lines are the test plant profiles that are correctly classified. The red lines are the test plant profiles that are misclassified as class 4. The classification uses one plant profile per feature vector.

PWRI section of 17 consecutive days. The results are presented in Table 3, with one plant profile per feature vector and with two plant profiles per feature vector (see Equation (6)).

Fault identification The confusion matrices for the fault identification on the faulty points of the test occurrences are presented in Table 4 with respectively one and two plant profiles per feature vector. The algorithm is used to classify the feature vectors included in the occurrences of abnormal situation used for testing for each of the five selected classes. The rows indicate the true class of the feature vectors and the columns indicate their predicted class. The MD column corresponds to the missed detections, i.e. to the feature vectors identified as normal.

4. DISCUSSION

The fault detection results in Table 3 show the ability of the AR normalisation to reduce the false detection rate. The results with one plant profile per feature vector validate the hypothesis that using the AR normalisation makes the algorithm less sensitive to noisy variations. Table 3 shows that false detections can be eliminated regardless of the normalisation chosen using more than one (e.g. two) plant profile per feature vectors to introduce information about the development of the faults, which reduces the impact of noisy variations in the detection. Nevertheless, increasing the number of plant profiles per feature vector has a drawback, since it increases the missed detection rate as can be seen in the column headed as MD in Table 4. The different faults are on average detected one sample later by the algorithm, compared to a classification with one plant profile per feature vector.

The impact of the normalisation on the fault identification is more interesting. Unlike simulated models where variability across fault occurrences is usually modelled by an additive white noise, occurrences of the same type of fault can differ quite markedly in industrial systems. Figures 4 and 5 show examples where the same fault exhibits different behaviours, with an impact on the fault signature in the measurements. Figure 4 focusses on class 2 where a

low suction pressure in the water system triggers a trip of P21. For some of the occurrences of class 2, this also leads to a trip of P22 as a consequence. Therefore, occurrences of the fault differ by the value of their P22 inlet flow (A_FZT_114_) that drops in the training occurrence while it stays constant in the test occurrence. Figure 5 focusses on class 3 where fuel change triggers a trip of P11 or P21 (or both). The amplitudes of the drops in the inlet and outlet flows of P22 (resp. A_FZT_114_ and A_FZT_139_) as well as in the flow transmitter A_FT_121_ vary significantly from one occurrence of the fault to another.

Figures 4 and 5 highlight how the variability in process measurements across fault occurrences can lead to erroneous fault identification (Table 4). Plant profiles of class 2 are misclassified as class 4 in Figure 4 and plant profiles of class 3 are misclassified as class 2 in Figure 5. The choice of the normalisation is of critical importance because mean-centering, N and NF standardisations emphasize variations that are large in absolute values, or large relatively to historical data available. Since historical data of the faults are limited on industrial plant, a statistical approach such a standardisation can fail to comprehend the potential variability of some variables due to external factors, and the importance given to those variations introduces a bias in the classification. Conversely, alarm thresholds constitute a reference that contains the range of critical variation of each variable. In both cases depicted by Figures 4 and 5, while conserving the variability in the measurements across occurrences, the AR normalisation weights the amplitude of this variability relatively to the allowed operating range of the variables, limiting the impact on the results of the classification.

Therefore, the AR normalisation approach leads to a FDD system that is less sensitive to noisy variations with a low false detection rate, and still able to perform early detection. Once detected, the accuracy of the fault identification with this approach is almost perfect even with variability across fault occurrences, which constitutes an improvement compared to the traditional normalisation methods.

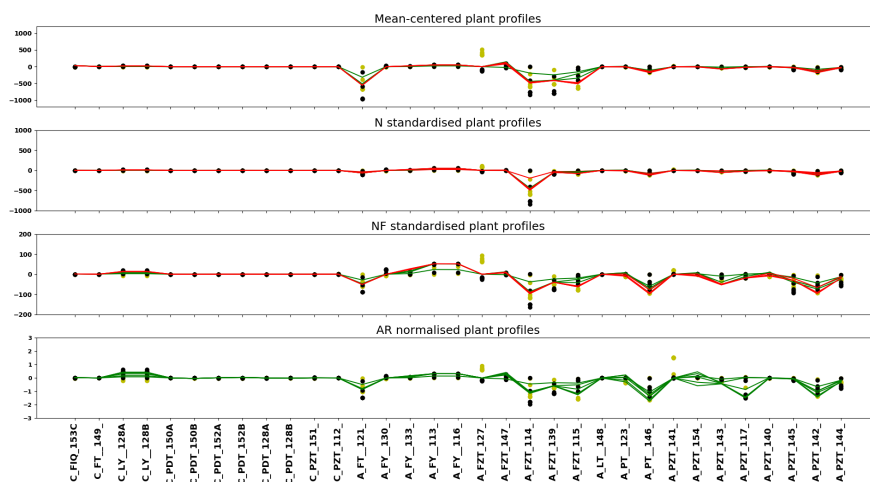


Fig. 5. Training plant profiles of class 2 (yellow points) and class 3 (black points) and test plant profiles of an abnormal situation B of class 3. The green lines are the test plant profiles that are correctly classified. The red lines are the test plant profiles that are misclassified as class 2. The classification uses one plant profile per feature vector.

5. CONCLUSION

Using the range between the upper and lower alarm thresholds as reference for the normalisation lowers the false detection rate and improves the accuracy of the identification. This is because the alarm-range normalisation places the variations of the process measurements in the context of safety criteria based on engineering considerations, which provides a better scaling of the features for the classification. On the contrary, statistical indicators such as the standard deviation do not distinguish critical variations from benign variations giving too much weight on the latter in the classification.

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