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12th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes SAFEPROCESS 2024

Ferrara, Italy, June 4 – 7, 2024

PROCEEDINGS

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FOREWORD

The IFAC SAFEPROCESS 2024 is continuing the successful series of symposia held in Baden-Baden (Germany, 1991), Helsinki (Finland, 1994), Hull (UK, 1997), Budapest (Hungary, 2000), Washington DC (USA, 2003), Beijing (China, 2006), Barcelona (Spain, 2009), Mexico City (Mexico, 2012), Paris (France, 2015), Warsaw (2018), and Paphos (Cyprus, 2022). The Department of Engineering of the University of Ferrara, Italy, organized the IFAC SAFEPROCESS 2024 in Ferrara, Italy, for the first time since its first edition, on June 4–7, 2024.

The theory and practice of control and technical diagnostics are facing big problems as the complexity of modern industrial systems and processes keeps growing. The need for greater reliability in their operation, control quality, and security is also growing. Early detection and diagnosis of faults and cyberattacks are critical to avoid performance degradation and damage to machinery or human life.

The SAFEPROCESS symposium is a triennial IFAC meeting and a major international gathering of leading academic and industry experts from all over the world. It aims at strengthening the contact between academia and industry to build up new networks and cultivate existing relations. High-level speakers have given talks on a wide spectrum of topics related to fault diagnosis, process supervision, safety monitoring, fault-tolerant control, cyber-security, as well as state-of-the-art applications and emerging research directions. The symposium has also served as a forum for young researchers, giving them the opportunity to present their scientific ambitions and work to an audience consisting of international technical diagnostics and control communities.

Fault diagnosis and fault-tolerant control have developed into major research areas at the intersection of system and control engineering, computer science, applied mathematics and statistics, or soft computing, as well as application fields such as mechanical, electrical, chemical, and aerospace engineering. IFAC is recognised as playing a crucial role in this aspect by launching a triennial symposium dedicated to this subject.

The SAFEPROCESS 2024 program can be accessed at https://www.safeprocess2024.eu/#. The program consisted of nineteen regular and five invited sessions on three parallel tracks. It also contained six keynote talks prepared by outstanding academics and industrials who introduced advanced results on fault diagnosis, fault-tolerant control, root cause analysis, and cyberattack prevention. In particular, Prof. Ron J. Patton (UK), from the Univ. of Hull, delivered the speech entitled “Offshore Wind Turbine Rotor Imbalance, a Fault-Tolerant Control Problem”; Prof. Christophe Combastel (FR), from the Univ. of Bordeaux, delivered the speech entitled “ Reachability and Filtering for Safe Processes: From Zonotopes to Functional Sets with Typed Symbols”; Prof. Roger Dixon (UK), from the Univ. of Birmingham, gave the talk “Fault Tolerance in Railways: “The Evolution of a Radical Next Generation Track Switch”; Dr. Steinert Olof (SE) from Scania, delivered the speech “Harnessing Data for Predictive Maintenance and Collaboration, Boost Innovation”; Prof. Biao Huang (CA), from the Univ. of Alberta, talked about “Advancing Causal Analysis for Fault Detection and Root Cause Analysis in Process Systems Engineering”; and Prof. Ping Zhang (DE), from the Univ. of Kaiserslautern-Landau, gave the talk “Detection and Avoidance of Cyber Attacks on Industrial Control Systems”.

The symposium received one hundred seventy-eight submissions, divided into three sets: one hundred forty regular papers, thirty-one invited papers, and seven invited sessions. The rejection rate for submissions was 23%. The symposium had one hundred eighty-seven participants, including one hundred twenty-two academics and sixty-five students. Regarding the statistics, we identified an average of 3.6 authors per paper. The number of participating countries was forty-eight. Regrettably, we failed to achieve a satisfactory balance between geographical regions. The countries with the most papers, in decreasing order, are China, France, Germany, Italy, Spain, Sweden, the United Kingdom, the United States of America, the Netherlands, and Mexico.

One pre-symposium tutorial, a roundtable, and a benchmark competition were also included in the technical program. As a result, Vasso Reppa from Delf University of Technology, Mayank S. Jha, and Didier Theilliol from the University of Lorraine organized the roundtable titled "Gnosis for Maintenance: From Diagnosis to Prognosis and Health-Aware Control." The meeting was very active, with comments and questions from more than fifty attendees in a two-hour session. Additionally, Eric Frisk, Daniel Jung, and Mattias Krysander from Linköping University organised a competition on fault detection and isolation techniques with incomplete data. The airflow system of an internal combustion engine was considered an industrial benchmark. The competition was intriguing and a good motivating example for young researchers. A two-hour special session presented the results of the six participants. The young researchers Nicolas Anselmi, Andrea Arici, Francesco Corrini, and Mirko Mazzolen from the University of Bergamo, Italy, took first place in the competition, and the two next classified also obtained a diploma.

Regarding the pre-symposium tutorials, three proposals were received; however, only one met the minimum registration quota defined by the organizers. Linlin Li from the University of Science and Technology Beijing, Zhiwen Chen from Central South University, and Steven X. Ding from the University of Duisburg-Essen integrated the tutorial, entitled "Control Theory-Informed Machine Learning for Fault Diagnosis in Dynamic Control Systems." The tutorial was free for students, and there were thirty-three attendees.

The symposium recognized three awards: the *Paul M. Frank Theory Paper Award* given to Louis Goupil, Louise Travé-Massuyès, Elodie Chanthery, Thibault Kohler, Sébastien Delautier for the paper entitled "Tree-Based Diagnosis Enhanced with Meta Knowledge Applied to Dynamic Systems"; the *IFAC Young Author Award* given to Henrik Sebastian Steude*, Lukas Moddemann, Alexander Diedrich, Jonas Ehrhardt, Oliver Niggemann for the paper entitled "Diagnosis Driven Anomaly Detection for Cyber-Physical Systems"; finally, the *Best Application Paper Award* was given to Andrea Mattioni, Lucas José da Silva Moreira, Herve Yves Guy Bernard Louis Roustan, Gildas Besancon, Mirko Fiacchini for the paper entitled "A step towards implementation of state observers in industrial aluminium smelters".

SAFEPROCESS 2024 was the first IFAC SAFEPROCESS symposium to be streamed thanks to the University of Ferrara YouTube channel, enabling researchers and practitioners to participate either physically or online. As a result, the sessions are still accessible through the complete playlist at www.youtube.com/playlist?list=PLL80i9P61J-O-4-Y79u-KKkoHybZw9d0k. The presentations provided participants with an invaluable opportunity to learn from the knowledge and experiences of world-renowned scientists and experts. Covering a range of exciting topics, these sessions generated ideas, concepts, and methods that will make future industrial systems and processes more efficient and safer.

As International Programme Committee Chair and General Chair, we are filled with immense pride and joy as we reflect on the success of this remarkable event. The hard work, dedication, and collaborative spirit of everyone involved have truly paid off, creating an unforgettable experience for all participants. We extend our heartfelt gratitude to all who contributed, and we look forward to many more successful IFAC SAFEPROCESS symposia in the future.

Cristina Verde
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Identification of relevant symptoms of performance degradation in industrial machines

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Abstract: In the last decades, manufacturing companies increasingly recognized the role of maintenance in guaranteeing high performances for their machines. At the same time, companies realized that, through the analysis of operational data, knowledge on the health status and performance of the machines could be generated, and maintenance-related optimizations and services could be offered to customers. In this setting, the identification of causes leading to degradation of key performance indicators (KPIs) of a machinery is of paramount importance in deciding what actions to take to improve machines performances. In this paper, we propose the use of symptomatology indicators that allow to automatically estimate symptoms of KPI decay in industrial machines. The effectiveness of the proposed symptomatology analysis is experimentally evaluated on real data coming from a set of four shrink wrappers, showing the benefits of the proposed indicators both on client and producer side.

Keywords: performances degradation, key performance indicator, symptomatology indicators

1. INTRODUCTION

Data collection and analysis are among the most discussed themes following the spreading of the fourth industrial revolution (Lamnabhi-Lagarrigue et al., 2017; Mazzoleni et al., 2022). Therefore, manufacturing companies are exploring with increasing interest the field of data-driven business models, thanks to the possibility to optimize their production processes (Thoben et al., 2017). Maintenance is among the fields that can benefit the most from this, both as an internal function and as a service offered to customers. Through the collection of selected data from the field and the definition of performance and health indicators, companies can have a clear picture of a machine behaviour, identifying early problems and preventing major failures that critically affect the business (Pech et al., 2021).

The integration of data-driven strategies in maintenance decision-making - being it internal or external - can contribute to improve several aspects of the company operations, both in industrial and safety-critical contexts (Valceschini et al., 2022b; Boni et al., 2023). For instance, new maintenance strategies can be introduced, moving from the corrective towards condition-based and/or predictive ones, also improving the preventive ones in the meantime (Converso et al., 2023; Valceschini et al., 2022a; Maurelli et al., 2024). Moreover, spare parts and workforce management can be optimized, reducing the spare parts consumption as well as improving the schedule of maintenance interventions. Also, this can impact machines design, which can be enhanced by studying the behaviours of the components during the actual machine's operating time. By knowing the health variation and studying failure causes and frequency, designer can apply modifications to reduce failures, prolong useful life and increase productivity (Sala et al., 2021). The definition of collection and processing approaches and performance/health indicators is fundamental to support such offering (Carvalho et al., 2019).

In this paper, we propose *symptomatology indicators* for automatically *estimating symptoms of performance degradation* in industrial machines. We show how the proposed indicators can be leveraged both on client and producer side, in order to effectively asses what actions to take for improving the monitored machine performances. Experimental results on four shrink wrappers show the benefits of the proposed symptomatology analysis.

The remainder of the paper is as follows. Section 2 presents the developed symptomatology indicators. In Section 3 the experimental results of the symptomatology analyses conducted on shrink wrappers, by means of the proposed indicators, are presented. Section 4 concludes the paper.

2. IDENTIFICATION OF KPI DECAY SYMPTOMS

Consider a dataset $\mathcal{D}$ of machine variables gathered at different time instants. Define the *set of interest* $\mathcal{X}$ as the collection of *variables of interest* $x \in \mathcal{X}$. For instance, $\mathcal{X}$ can be defined as the set of machine alarms, with x being a monitored alarm in $\mathcal{X}$. The *measure of incidence* $I_x \in \mathbb{R}_{\geq 0}$ is defined as the measure of a certain characteristic of x as computed from $\mathcal{D}$, such as occurrence measures, time durations, etc. Considering a threshold θ for a key performance indicator (KPI) of the machinery, the measure of incidence I_x can be split in two terms:

- $I_x^+ \in \mathbb{R}_{\geq 0}$, which measures the incidence of a characteristic of x *above* θ;

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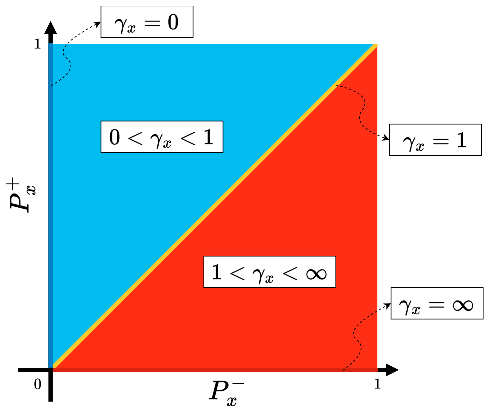

Fig. 1. Possible cases in (3) for the γ_x indicator. The variables x which are eligible as symptoms of a KPI degradation below the given threshold θ lie in the red areas ($\gamma_x > 1$).

- $I_x^- \in \mathbb{R}_{\geq 0}$, which measures the incidence of a characteristic of x *below* θ.

Define as a *symptom of the degradation of a machine KPI* the evidence of the cause (or causes) that led the KPI to degrade.

Given a dataset $\mathcal{D}$ and a set of interest $\mathcal{X}$ for a machinery, the aim is to identify what variables of interest $x \in \mathcal{X}$ are *the most symptomatic of a KPI degradation*, according to a chosen measure of incidence I_x computed from $\mathcal{D}$.

2.1 Definition of the symptomatology indicators

Given a KPI threshold θ and the measures of incidence I_x^+ and I_x^- of the variables of interest $x \in \mathcal{X}$, the *incidence rates* of x above and below θ are defined, respectively, as

$$P_x^+ \triangleq \frac{I_x^+}{\sum_{y\in\mathcal{X}} I_y^+}, \quad P_x^- \triangleq \frac{I_x^-}{\sum_{y\in\mathcal{X}} I_y^-}. \tag{1a}$$

The incidence rates $P_x^+, P_x^- \in [0,1]$ represent the percentages of incidence of x respectively above and below a fixed KPI threshold θ. The larger P_x^- is with respect to P_x^+, the more eligible x is as symptom of a KPI decay below θ. So, we define the γ_x indicator as follows:

$$\gamma_x \triangleq \frac{P_x^-}{P_x^+}, \tag{2}$$

with $\gamma_x \in \mathbb{R}_+$. Hence, the γ indicator measures *how much more x incides below than above a fixed KPI threshold θ*. In particular, the following cases can occur:

$$\begin{cases} \gamma_x = 0, & x \text{ incides only above } \theta; \\ 0 < \gamma_x < 1, & x \text{ incides more above than below } \theta; \\ \gamma_x = 1, & x \text{ incides equally above and below } \theta; \\ 1 < \gamma_x < \infty, & x \text{ incides more below than above } \theta; \\ \gamma_x = \infty, & x \text{ incides only below } \theta. \end{cases} \tag{3}$$

A graphical visualization of the cases in (3) is shown in Figure 1. From (3), it is trivial to notice that the variables in $\mathcal{X}$ eligible as symptoms of a KPI decay below θ are the x such that $\gamma_x > 1$, that is the ones with a greater incidence rate below θ than above θ (lying in red areas in Figure 1).

However, being (2) based solely on the ratio between the incidence rates P_x^-, P_x^+, the information about their *magnitudes*, that can be relevant for the analysis, is lost. For instance, consider $x_1, x_2 \in \mathcal{X}$ with $P_{x_1}^- \gg P_{x_2}^-$, such that $1 < \gamma_{x_1} < \gamma_{x_2}$: then, indicator (2) estimates x_2 as a more relevant symptom compared to x_1, without considering the extremely higher incidence rate of x_1 below θ.

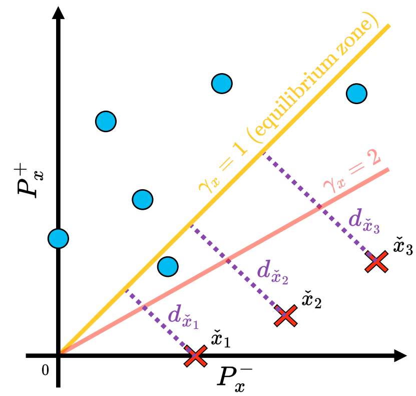

Fig. 2. Distances $d_{\check{x}}$ (purple dotted lines) of the variables $\check{x}$ (red crosses), from the equilibrium zone. In this example $\vartheta = 2$, so that the $\check{x}$ are such that $\gamma_{\check{x}} \geq 2$, while the other variables (blue circles) are not considered in the analysis by means of the d indicator.

In order to include in the symptomatology analysis the information on the magnitudes of the incidence rates in (1), consider first only the variables x with an arbitrary large value γ_x. As noticed above, by looking at (3), the variables of interest x such that $\gamma_x > 1$ are the most relevant for the analysis of a KPI decay, according to the indicator (2). Hence, the set $\check{\mathcal{X}}$ of the variables of interest $\check{x}$, obtained filtering $\mathcal{X}$ by means of (2), is defined as

$$\check{\mathcal{X}} \triangleq \{\check{x} \,|\, \check{x} \in \mathcal{X},\, \gamma_{\check{x}} \geq \vartheta,\, \vartheta > 1\}, \tag{4}$$

where ϑ is an arbitrary threshold for the variables selection. The larger the threshold ϑ, the stricter the selection of the symptomatic variables $\check{x} \in \check{\mathcal{X}}$.

Given the variables $\check{x}$, the magnitudes of the corresponding incidence rates $P_{\check{x}}^+, P_{\check{x}}^-$ are leveraged to compute the distances of the $\check{x}$ from the *equilibrium zone*, that is the locus of points such that $\gamma_x = 1$, i.e. when $P_x^+ = P_x^-$. From geometrical properties, the distance of a variable $\check{x}$ from the equilibrium zone is defined as

$$d_{\check{x}} \triangleq \frac{P_{\check{x}}^- - P_{\check{x}}^+}{\sqrt{2}}, \tag{5}$$

with $d_{\check{x}} \in \left(0, 1/\sqrt{2}\,\right]$. Figure 2 shows a graphical example of the distances $d_{\check{x}}$ from the equilibrium zone, with $\vartheta = 2$. The indicator (5) can be interpreted as a measure of *how much a variable $\check{x}$ is distant from the equilibrium zone*. The higher $d_{\check{x}}$, the more relevant $\check{x}$ is as a symptom of KPI degradation below the given threshold θ.

However, the d indicator may mask the effect of variables with lower incidence rates below θ, but with larger values of the γ indicator. Consider the example shown in Figure 2: the variable $\check{x}_1$ is the least relevant in the analysis according to the indicator (5), since $d_{\check{x}_1} < d_{\check{x}_2} < d_{\check{x}_3}$. However, at the same time, $\check{x}_1$ has the largest value of the indicator (5), as $\gamma_{\check{x}_1} = \infty$ since it lies on the P_x^- axis (see Figure 1 for reference), meaning that variable $\check{x}_1$ has incidence only below the KPI threshold θ, see (3). The idea is then to *combine the information* provided by *both* indicators (2) and (5), leveraging the respective advantages. So, let the *symptomatology indicator* $\delta_{\check{x}}$ be defined as

$$\delta_{\check{x}} \triangleq \gamma_{\check{x}} \cdot \frac{d_{\check{x}}}{\sum_{\check{y}\in\check{\mathcal{X}}} d_{\check{y}}}, \tag{6}$$

with $\delta_{\check{x}} \in \mathbb{R}_+$. The indicator (6) is a single and *aggregate indicator* that measures how much a variable of interest $\check{x} \in \check{\mathcal{X}}$ is *symptomatic of a KPI degradation below a chosen threshold* θ. The higher the value of $\delta_{\check{x}}$, the more the variable $\check{x}$ is relevant as symptom of a KPI decay below θ for the monitored machinery. Algorithm 1 summarizes the steps needed for the computation of the indicator (6).

Algorithm 1 Symptomatology indicator

Inputs: variables of interest $x \in \mathcal{X}$, KPI threshold θ, variables filtering threshold ϑ

Output: δ indicator values for the variables $\check{x} \in \check{\mathcal{X}}$

```
for each x ∈ 𝒳
    Compute the measures of incidence I_x^+, I_x^- w.r.t. θ
    Compute the incidence rates P_x^+, P_x^- via (1)
    Compute γ_x via (6)
end for
Filter 𝒳 to obtain 𝒳̌, as defined in (4)
for each x̌ ∈ 𝒳̌
    Compute d_x̌ via (5)
    Compute δ_x̌ via (6)
end for
```

Notice that the symptomatology indicator as defined in (6) allows to evaluate symptoms of a KPI degradation with respect to a fixed threshold θ, making the symptomatology analysis dependent on the specific considered threshold. In the next section, we show how the symptomatology analysis by means of (6) can be carried out without depending on a specific threshold θ. Furthermore, we show how the analysis results can be leveraged on both client and producer side.

2.2 Use of the symptomatology indicators

The symptomatology indicator (6) is a powerful instrument for estimating what variables of interest are most symptomatic of a KPI degradation below a given threshold θ, for the monitored machine. However, it lacks generality, since it is strictly dependent on a specific KPI threshold θ. In order to untie the symptomatology indicator from such dependence, the idea is to carry out the symptomatology analysis by means (6) for different values of the KPI threshold θ, and then combining the results.

In order to do so, define the set Θ of N_θ KPI thresholds θ to evaluate. From now on, we denote the results referred to a specific threshold by using θ as apex. For each threshold $\theta \in \Theta$, identify the corresponding set $\check{\mathcal{X}}^\theta$ and compute $\delta^\theta_{\check{x}}$ for the variables in the set, by means of Algorithm 1. The obtained symptomatology indicator values are not comparable from one threshold to another, because the N_θ obtained sets $\check{\mathcal{X}}^\theta$ are (likely) different, with *different variables and a different number of elements*. For example, considering a symptomatic variable $\check{x}$ such that $\delta^{\theta_1}_{\check{x}} = \delta^{\theta_2}_{\check{x}}$, with $\theta_1 \neq \theta_2$, the two indicators values are not comparable. Indeed, it can not be stated a priori that $\check{x}$ is *equally* relevant as a symptom for a KPI decay with respect to θ_1 and θ_2. In fact, it may be that $\check{x}$ is simultaneously the most and the least relevant symptom with respect to θ_1 and θ_2 respectively (or vice versa), when considering all the other variables in $\check{\mathcal{X}}^{\theta_1}$ and $\check{\mathcal{X}}^{\theta_2}$.

Hence, in order to make the symptomatology analysis results comparable between different thresholds, the θ-dependent $\delta^\theta_{\check{x}}$ indicator values are normalized as follows:

$$\tilde{\delta}^\theta_{\check{x}} \triangleq \frac{\delta^\theta_{\check{x}}}{\sum_{\check{y}\in\check{\mathcal{X}}^\theta} \delta^\theta_{\check{y}}}, \tag{7}$$

with $\tilde{\delta}^\theta_{\check{x}} \in (0,1]$. The result is a normalized symptomatology indicator that allows *to compare results referring to different thresholds*. Notice that the identified symptoms may differ between the considered thresholds in the set Θ. Then, define the set of *all the symptomatic variables per threshold*, without repetitions, as:

$$\check{\mathcal{X}}^m \triangleq \bigcup_{\theta\in\Theta} \check{\mathcal{X}}^\theta = \left\{ \check{x} \,|\, \exists\, \theta \in \Theta : \check{x} \in \check{\mathcal{X}}^\theta \right\}. \tag{8}$$

Given the set $\check{\mathcal{X}}^m$, we define the *machine symptomatology indicator* δ^m as:

$$\delta^m_{\check{x}} \triangleq \frac{\sum_{\theta\in\Theta} \tilde{\delta}^\theta_{\check{x}}}{\sum_{\check{y}\in\check{\mathcal{X}}^m} \sum_{\theta\in\Theta} \tilde{\delta}^\theta_{\check{y}}}, \tag{9}$$

with $\delta^m_{\check{x}} \in (0,1]$. The δ^m indicator measures how much a variable of interest is *generally symptomatic of a KPI degradation for the monitored machinery*, thus abstracting the analysis from the concept of KPI threshold θ. The higher the δ^m indicator value of a variable $\check{x}$, the more $\check{x}$ is a relevant symptom of a KPI degradation of the machine. Algorithm 2 summarizes the steps needed to compute the machine symptomatology indicator (9).

Algorithm 2 Machine symptomatology indicator

Inputs: inputs of Algorithm 1, KPI thresholds $\theta \in \Theta$

Output: δ^m indicator values for the variables $\check{x} \in \check{\mathcal{X}}^m$

```
for each θ ∈ Θ
    Compute δ_x̌^θ by means of Algorithm 1
    Compute δ̃_x̌^θ via (7)
end for
Obtain the set 𝒳̌^m, as defined in (8)
for each x̌ ∈ 𝒳̌^m
    Compute δ_x̌^m via (9)
end for
```

The symptomatology analysis results obtained by means of (9) can be of particular aid on the *client side*. Indeed, the variables with the highest values of the (9) are the ones to which the client *must pay more attention and take care of*, to enhance the machine performance. For instance, by considering the *machinery alarms* as variables of interest x, the alarms with highest δ^m indicator values may give an indication to the client on what machine components are faulty and need maintenance or replacement.

By taking a step further, consider now a set $\mathcal{M}$ of similar machines m. For each machinery $m \in \mathcal{M}$ a symptomatology analysis is carried out and the δ^m indicator values are computed via Algorithm 2. As before, we can group the machines symptoms in the sets $\check{\mathcal{X}}^m$ into a unique set defined as

$$\check{\mathcal{X}}^{DB} \triangleq \bigcup_{m\in\mathcal{M}} \check{\mathcal{X}}^m = \left\{ \check{x} \,|\, \exists\, m \in \mathcal{M} : \check{x} \in \check{\mathcal{X}}^m \right\}. \tag{10}$$

Given the set $\check{\mathcal{X}}^{DB}$ in (10), we define the *database symptomatology indicator* $\delta^{DB} \in (0,1]$ as:

$$\delta_{\check{x}}^{DB} \triangleq \frac{\sum_{m\in\mathcal{M}} \delta_{\check{x}}^{m}}{\sum_{\check{y}\in\check{\mathcal{X}}^{DB}} \sum_{m\in\mathcal{M}} \delta_{\check{y}}^{m}}, \tag{11}$$

The indicator (11) measures how much a variable of interest is *symptomatic of a KPI degradation for the machines in* $\mathcal{M}$. Thus, the database indicator generalizes the symptomatology analysis to a *type* of machinery, rather than to a single instance of that machine type. The indicator (11) can be used to create a *symptomatology database*, where the most relevant symptoms of a KPI degradation for similar machinery are gathered.

Algorithm 3 Database symptomatology indicator δ^{DB} computation

Inputs: inputs of Algorithm 2, similar machines $m \in \mathcal{M}$
Output: δ^{DB} indicator values for the variables $\check{x} \in \check{\mathcal{X}}^{DB}$

for each $m \in \mathcal{M}$
  Compute $\delta_{\check{x}}^{m}$ by means of Algorithm 2
end for
Obtain the set $\check{\mathcal{X}}^{DB}$, as defined in (10)
for each $\check{x} \in \check{\mathcal{X}}^{DB}$
  Compute $\delta_{\check{x}}^{DB}$ via (11)
end for

The indicator (11) can be particularly helpful on the *producer side*. Indeed, the most relevant symptoms stored in the symptomatology database give an indication to the producer on *how to improve the design of the produced machines to achieve better performances*. For instance, consider again the machine alarms as variables of interest. The alarms with the highest values of (11) can point out the most critical components of the produced machines, suggesting a more frequent maintenance of such components or their replacement in the machines production line.

3. APPLICATION TO SHRINK WRAPPERS

The considered application regards the estimation of the symptoms of a KPI degradation of four packaging machines, namely shrink wrappers (SWs), which belong to the same production line. First, Section 3.1 describes the experimental set-up and reports the main goals of the analysis. Then, in Section 3.2 we present the results obtained conducting a symptomatology analysis via the indicators (9) and (11).

3.1 Shrink wrapper design, monitored KPIs and objectives

The considered SWs consist of four serial working zones:

(1) *entry zone*: the input products to be packed are canalized in rows and moved by conveyor belts;
(2) *separator zone*: the products are grouped according to a pre-set production recipe;
(3) *packing zone*: a tray is added to the group of products, which is then bundled by wrapping it with a thin plastic film;
(4) *shrink tunnel*: heat is applied in order to make the wrapping film to shrink tightly over the packed group.

Figure 3 shows a schematic of the SWs working process. Each SW is equipped with a number of sensors to monitor the machine health status, and to report malfunctions by triggering specific alarms.

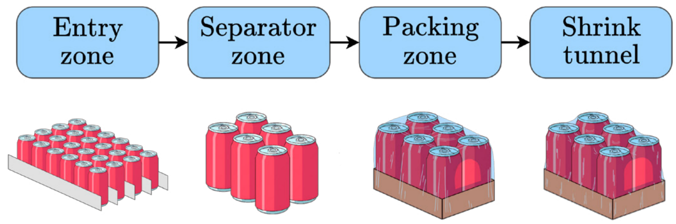

Fig. 3. Schematic of the considered SWs working process.

The SWs performances are evaluated by means of different KPIs. The value at a time instant t of a KPI is given by a moving average, which is based on the past 60 KPI values computed per minute, up to instant t. When the machine starts, the KPI value at t is computed by means of the available per minute values, if their number is less then 60. When the SW is turned off, the KPIs computation stops. The KPI considered in the following analysis is the *overall equipment effectiveness* R_s, computed by the SW producer by considering the efficiency of a SW in terms of percentage of planned production time, without unexpected technical difficulties or maintenance needs (Muchiri and Pintelon, 2008). For the SW producer, *a good efficiency guarantee* is when $R_s \geq 94\%$. The aims of the SWs analysis are:

O1) to give indications to the *client* on what to do when the R_s indicator does not meet the expectations;
O2) to give indications to the *producer* on how the machine design can be enhanced to improve the SWs performances, in terms of R_s.

3.2 Experimental results of the symptomatology analyses

The symptomatology analyses were conducted on four similar shrink wrappers produced by the same manufacturer, each belonging to different clients. Hence, the set of monitored machines is $\mathcal{M} = \{\mathrm{SW1}, \mathrm{SW2}, \mathrm{SW3}, \mathrm{SW4}\}$. The considered SWs datasets gather the information measured by the machines sensors, such as alarms count and duration, external temperature, used recipe and so on. The available data were gathered in the same period of eight months, every five minutes during the working activity of the SWs.

The considered set of interest $\mathcal{X}$ consists in the *stop reasons* of the machines, with a stop reason being an *alarm that triggered a SW to stop working*. So, the considered variables of interest $x \in \mathcal{X}$ are the alarms which are identified as stop reasons in the SWs datasets. Table 1 shows a partial list of the identified SWs stop reasons, each with an associated identifier (ID). Note that when a SW is working normally without downtimes, the stop reason ID is set to 0.

The chosen measure of incidence I_x for the stop reasons in $\mathcal{X}$ is the *last occurrence* measure, which is based on counting only the *last instance of* x *in an interval of its consecutive occurrences in time order*. The idea is that if a stop reason occurs for more consecutive timestamps, then the last occurrence in the interval is associated to the least R_s value of the sequence. This allows to analyse the machines stop reasons based on the actual corresponding R_s degradation. Figure 4 shows the difference in choosing total and last occurrence as measure of incidence for the stop reasons, highlighting the higher effectiveness of the latter in capturing the actual decay of the R_s indicator.

Table 1. Stop reasons ID and name.

ID	Stop reason name
1	Anomaly at cardboards enable zone
2	Anomaly at cardboards running zone
3	Cardboards reserve end
4	Drive shutdown – Film wrapper
5	Electronic divider at a standstill
6	Infeed conveyor off
7	No cardboard in ramp 1
8	No film on the pack
9	Outlet conveyor off
10	Outlet obstruction
11	Pack down in film enable area
12	Product flow end
13	Separator zone anomalous situation
14	Stop command by operator
0	*SW working normally (no stop reasons)*

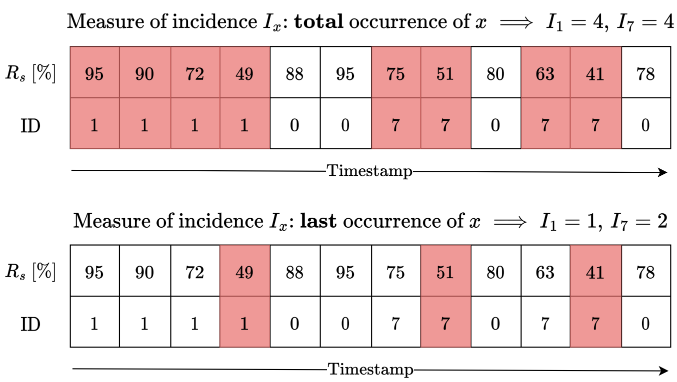

Fig. 4. Total and last occurrence as measure of incidence for the stop reasons. Red cells point out the data considered for the analyses in the two cases. The last occurrence measure better captures the actual R_s degradation, here with respect to the stop reasons 1 and 7.

The variables filtering threshold is set to $\vartheta = 2$. Hence, for each SW, the sets $\breve{\mathcal{X}}^{\theta}$, gathering the most relevant symptoms of the R_s degradation with respect to a threshold θ, consist of the stop reasons such that the γ_x indicator in (2) has at least value 2, see (4). In other words, for the computation via Algorithm 1 of the symptomatology indicator $\delta_{\breve{x}}$ in (6), the only considered stop reasons are those whose incidence rate below the R_s threshold θ is at least double than their incidence rate above such threshold.

In order to achieve objective O1, the machine symptomatology indicator δ^m in (9) is leveraged. For each SW in $\mathcal{M}$, the δ^m indicator for the stop reasons was computed by means of Algorithm 2, by considering $N_\theta = 94$ different R_s thresholds in the set $\Theta = \{1, 2, \dots, 94\}$, see (8).

Figure 5 shows the symptomatology analyses results obtained by means of the (9) for the considered machines n $\mathcal{M}$. Generally, for all the SWs, it can be noted how the most relevant symptom has a δ^m value which is particularly larger if compared to the other ones. This highlights how the most symptomatic stop reason has a great importance in pointing out the possible causes for the R_s degradation.

In particular, SW3 is the one that exhibited the highest gap between the first two most symptomatic stop reasons, with δ_3^m being seven times larger than δ_2^m. Stop reason 3 refers

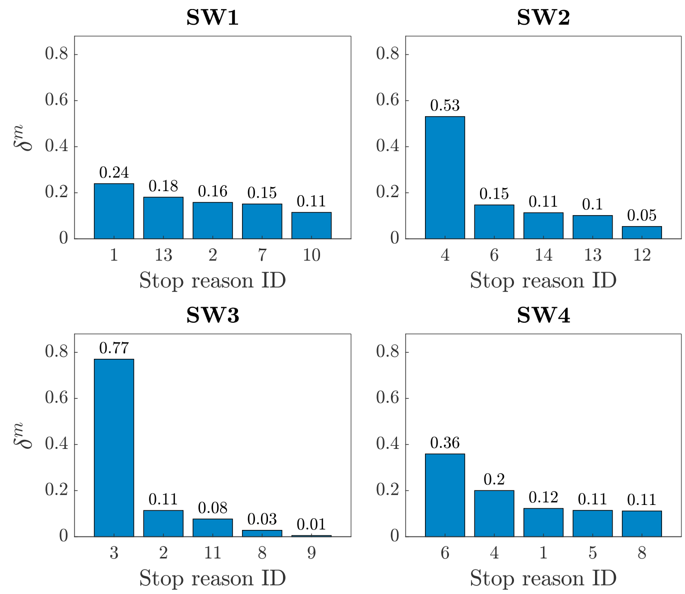

Fig. 5. Machine symptomatology indicator δ^m in (9) for the SWs in $\mathcal{M}$ with respect to the R_s KPI, considering the machine stop reasons as variables of interest. The five stop reasons identified as the most relevant symptoms of R_s degradation for each SW are shown.

to the lack of trays that have to be applied to the group of products, hence its highest estimated symptomatology gives an indication to the SW3 client to pay more attention to the provision of trays to the machine. Instead, the analysis conducted on SW1 pointed out the stop reasons 1 and 13 as the most relevant symptoms of R_s degradation, which refer to an error in a group of products position or size, in packing and separator zone respectively. Generally, such errors are due to faults on the sensors used to pack the products, thus suggesting the replacement of such sensors or their more frequent and careful maintenance.

For all the considered SWs in $\mathcal{M}$, *the results of the symptomatology analyses highlighted stop reasons related to machines problems that are well-known by the expert technicians of the clients*. Therefore, such results corroborates the effectiveness of the δ^m indicator in (9) in automatically estimating the most relevant symptoms of performances degradation in industrial machines.

The database symptomatology indicator δ^{DB} defined in (11) was employed to achieve objective O2. Figure 6 shows the SW symptomatology database obtained computing (11) by means of Algorithm 3. In the obtained database, the stop reason 3 is identified as the most relevant symptom of the R_s indicator degradation among the SWs in $\mathcal{M}$, although it appears as a symptom *only* for SW3, as shown in Figure 5. This is due both to the particularly high value of δ_3^m and to *the limited number of considered SWs*, which does not allow to effectively generalize the analysis. Hence, in this case, the results based on the δ^{DB} indicator (11) turns out to be biased with respect to the most symptomatic stop reason of SW3. Beyond this, notice how the other highest δ^{DB} indicator values are associated to the *most recurrent symptomatic stop reasons in the SWs*, thus highlighting the symptoms of the R_s decay that are *in common* between the SWs.

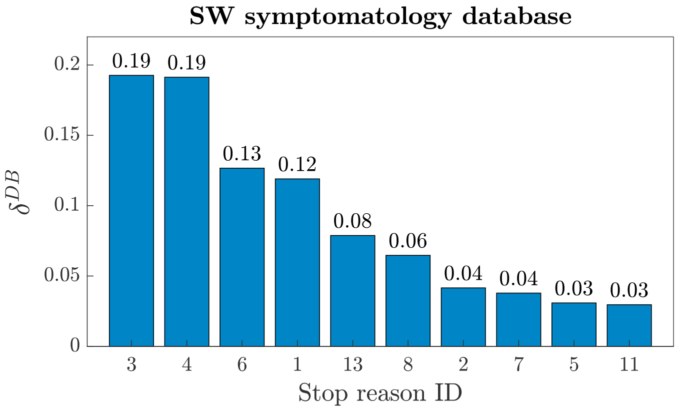

Fig. 6. Symptomatology database for the SWs based on indicator δ^{DB} in (11) with respect to the R_s KPI, considering the machine stop reasons as variables of interest. The ten stop reasons identified as the most relevant symptoms of R_s degradation over all the machines are shown.

One of the main R_s degradation symptoms in the obtained symptomatology database is the stop reason 4, which indicates that the driver of the brushless motor connected to the film wrapper (packing zone) is blocked. Such problem can be due to software issues in the microcontroller of the motor driver, hence pointing out to the SWs producer the need to check the corresponding code for any errors or bugs that may be causing the issue. As for stop reasons 1, 6 and 13, they all refer to problems in the position or size of the group of products, in different SW zone. In order to limit such issues, the producer may consider improvements in the produced SWs design. For instance, the number of sensors used to pack the products may be increased, or they can be substituted with more reliable ones.

The obtained *symptomatology database highlights issues in the SWs design that are known to the producer of the considered SWs*, thus confirming the effectiveness of the δ^{DB} indicator (11), despite the limited number of analysed SWs. The above presented results show how the machine and database symptomatology indicators can be particularly useful in analysing and pointing out problems in industrial machines, both on client and producer side. Clients can leverage the δ^m indicator in (9) to spot issues in new acquired systems, for which sufficient experience and knowledge are not yet available. Besides, a symptomatology database based on the δ^{DB} indicator in (11) can help manufacturers in improving the design of the produced machines, by pointing out common and most critical symptoms of performances degradation to treat.

4. CONCLUSIONS

This paper presented the use of symptomatology indicators to automatically estimate the symptoms of a KPI degradation in industrial machineries. Symptomatology analyses conducted on a set of four shrink wrappers highlighted the benefits of the defined indicators both on client and producer side. At the same time, the experimental results show how such indicators allow to make decisions more efficiently on possible actions to improve performances of the industrial machines. Future research is devoted to improve the symptomatology indicators accuracy, and to leverage them for predictive maintenance purposes.

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