Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 55-6 (2022) 778–783

Experimental fault detection of input gripping pliers in bottling plants

N. Valceschini *, **M. Mazzoleni** *, **L. Pitturelli** *, **F. Previdi** *

* *Department of Management, Information and Production engineering University of Bergamo, via Marconi 5, 24044 Dalmine (BG), Italy (e-mail: mirko.mazzoleni@unibg.it).*

Abstract: This paper presents a signal-based fault detection scheme for input gripping pliers of the blow molding machine in plastic bottling plants, using accelerometers data. The focus of the diagnosis is on the bearings that support the pliers movements on their mechanical cam. The rationale of the algorithm lies in interpreting the pliers' bearings as the balls in a traditional rolling bearing. Then, strategies inspired by bearing diagnosis are employed and adapted to the specific case of this work. The developed algorithm is validated with experimental tests, following a fault injection step, directly on the real blow molding machine.

Keywords: Fault detection; Mechatronic systems

1. INTRODUCTION

A bottling plant is a complex system that manages the entire production cycle for the sale of beverages. These plants can be large, distributed, and have a complex layout, see Struss and Ertl (2009). This work focuses on the production process of PolyEthylene Terephthalate (PET) plastic bottles. In this case, the input material is usually a rigid plastic preform. The process is composed by a series of sequential operations, covering e.g.: (i) preform feeding; (ii) heating; (iv) blowing; (iv) bottles filling and capping; (v) labeling; (vi) transportation along the production line; (vii) packaging and (viii) palletizing, see Figure 1. Each one of these processing steps is performed by a specialized machine, with their respective mechanical and electrical components. These machines are most of the times independently controlled, and their synchronization is performed during the first setup of the plant by an expert operator.

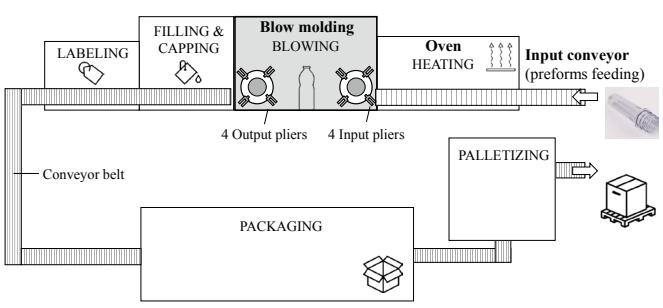

Fig. 1. Example of a bottling plant with main machines. The blow molding machine is highlighted as the main machine considered in this work.

The entire process stops if a machine or a component fails in one the main production steps, often causing large wastes of wrecked bottles, liquid and caps. Furthermore, if e.g., bottles get stuck in the blow molding machine, the operator has to manually extract them from the molds or from the pliers, wasting a lot of useful production time. As an example, the filling and capping machine stops if there is a lack of bottles from the input pliers, or if there is a tailback of filled bottles at output pliers. The works of Tsarouhas (2012); Castro and Araujo (2012) showed how the unscheduled downtime in bottling plants can vary between 10% and 60% of the total production time. Thus, a fault diagnosis system is highly envisaged to reduce (and prevent) the time wastes in this kind of production lines.

The concept of fault diagnosis refers to the general usage of specific techniques to assess the status of a system with respect to its possible faults. Fault diagnosis entails the following essential tasks Mazzoleni et al. (2021); Varga (2017): (i) Fault Detection (FD); (ii) fault isolation; (iii) fault estimation and (iv) fault identification. Fault diagnosis methodologies can be mainly divided into: (i) model-based; (ii) signal-based; (iii) knowledge-based. Model-based approaches make use of a model of the system dynamics to detect inconsistencies with actual measured data Ding (2013). Signal-based approaches lie on the assumption that certain process signals carry information about the faults to be detected; then, a fault symptom is extracted from those signals, see Randall (2011). In knowledge-based methods, there is not a priori behaviour or pattern to be compared with the actual measurements. Instead, the fault information is supposed to be hidden in the data, and has to be extracted, usually by machine learning or statistical techniques, as in Mazzoleni et al. (2019); Mazzoleni et al. (2018). Regarding the machine learning context, current research literature is focusing on transfer learning and dataset shift problems, see Valceschini et al. (2021); Lei et al. (2020).

Fault diagnosis approaches in bottling plants have been relatively little addressed in the literature. Models of chained production lines can be found in the queuing theory of Papadopoulos and Heavey (1996). In Voigt et al. (2015), the authors focused on the diagnosis of the fill-

10.1016/j.ifacol.2022.07.221

ing machine, by employing a type of model-based fault diagnosis known as consistency-based approach. Here, the whole plant has been modeled with a set of components, and anomalies in the bottle transport flows are detected. An alternative modeling of the plant is proposed in Renganathan and Bhaskar (2013), where Petri-nets are employed for the detection of bottle overflows, improver filling valve operation and Infra-Red (IR) sensors monitoring. A decision-tree expert system is employed in Troupis et al. (1995), where transition time data are used for detecting faults in a brewery plant.

This work presents a *signal-based FD scheme for gripping pliers in bottling plants*. The pliers are present in the blow molding machine. The aim of the input and output pliers is to carry the preforms and the bottles, respectively, from the input conveyor belt into the blow molding machine and from the blow molding machine to further processing. The presented literature investigated the modeling the entire production process, mainly with an higher-level outlook and a focus on the flow of the bottles material. Instead, we focus our attention on a *specific component and on its working behavior*. The aim of this work is to *detect the degradation of the posterior bearings* used for the movement of pliers that carry the heated preforms from the oven into the molds of the blow molding machine. The devised FD algorithm interprets the pliers' bearing like the ball element in a traditional rolling bearing. Thanks to this interpretation, signal processing techniques can be employed on accelerometers data to extract diagnostic information. The application of the proposed diagnostic algorithm on experimental data shows the goodness of the method.

The paper is organized as follows. The experimental setup and fault injection procedure are described in 2. The main idea underlying the proposed fault detection algorithm is highlighted in 3. Section 4 presents the experimental results. Section 5 concludes the paper.

2. EXPERIMENTAL SETUP

2.1 System description

The bottling plant under consideration is composed by the following components, see also Figure 2:

(1) an *input conveyor*, that feeds the raw plastic preforms into the plant;
(2) an *oven*, used to heat the plastic preforms;
(3) a set of *input gripping pliers*, that take the overheat preforms and bring them into the blow molding stage;
(4) a blow molding machine, that blows the preforms, now fixed in a mold, into the final bottle format;
(5) a set of *output gripping pliers*, that take the blown bottles from the blow molding machine and bring them into the filling stage;
(6) a *filling and capping machine*, that fills the blown bottles with a liquid and put the caps;
(7) a *conveyor belt*, that transports the filled and capped bottles;
(8) a *packing and palletizing machines*, that create bottles packs and arrange them for loading and transportation.

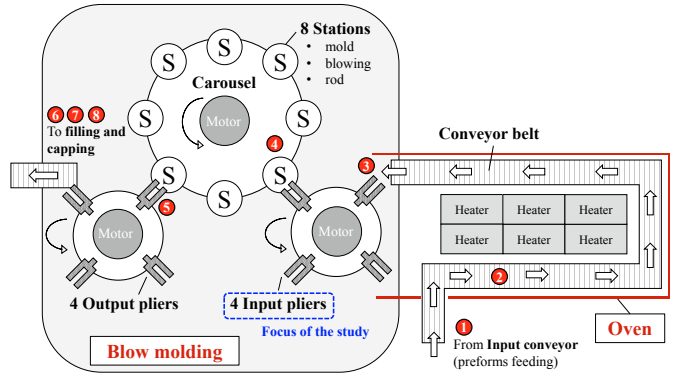

Fig. 2. Schematic of the oven and blow molding machines for a plastic bottling plant. The steps of the production process, from (1) to (8), are highlighted with respect to the components responsible for each step.

In this work, we consider only the blow molding machine, see Figure 2. This machine is composed by three important components:

- the *carousel*, a rotating component that supports one or more stations;
- the *stations*, i.e. the main component for blowing the preforms. Each station is made up of:
  - a *mold*, that defines the form of the blown bottle;
  - a *rod*, which is used to stretch the heated preform prior to its blowing;
  - the blowing system;
- the output and input *gripping pliers* (the main focus of this study).

The blow molding machine under consideration has 8 stations and 4 input/output pliers. An example of a gripping plier is depicted in Figure 3-(left). The pliers lie on a mechanical cam via two sets of bearings: two posterior and a frontal one. The arms of the plier, responsible for the gripping, are connected to the frontal bearing. The two sets of bearings (posterior and frontal) are connected by two springs. The cam is made in such a way that, when the springs stretch (i.e. when the distance between the two set of bearings is large), the plier arms open due to the retracting of the springs. When this happens, the preform can enter between the arms. Then, the cam mechanics release the tension on the springs and the arms close, this time holding the preform. This behaviour is schematized in Figure 4.

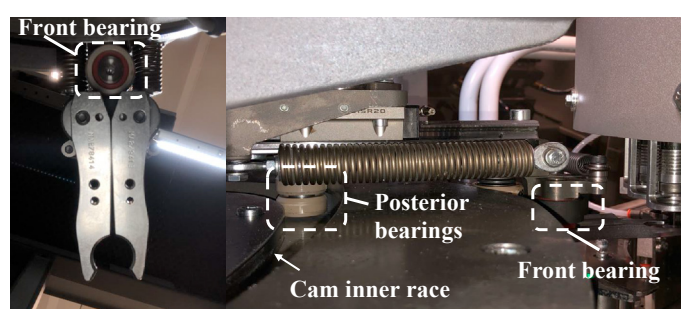

Fig. 3. (Left) Upper-view of an input gripping plier with front bearing detail. (Right) Upside down side-view with posterior bearings, springs and cam detail.

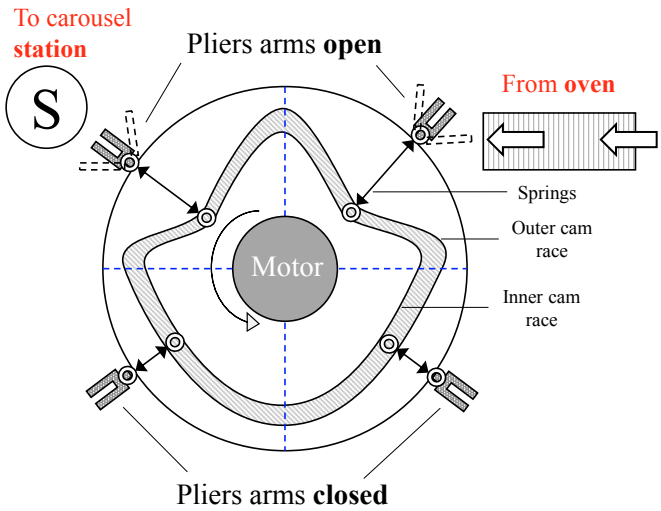

Fig. 4. Opening and closing mechanism of the pliers arms as function of the plier position on the cam.

When the springs are stretched and the pliers arms open, the posterior and frontal bearings are tightly attached to the cam structure. In all other cases, the bearings may not be always in contact with the cam. Thus, we expect to detect a damage on the posterior bearings in the first case, i.e. when the plier arms are fully open. From Figure 4 we observe that the pliers arms are open when the plier has to take a preform from the oven, or when it has to release a preform inside the mold of a station.

2.2 Fault injection and testing procedure

A damage was injected on posterior bearings in the plier mechanism, by partially removing material from the bearing surface, see Figure 5.

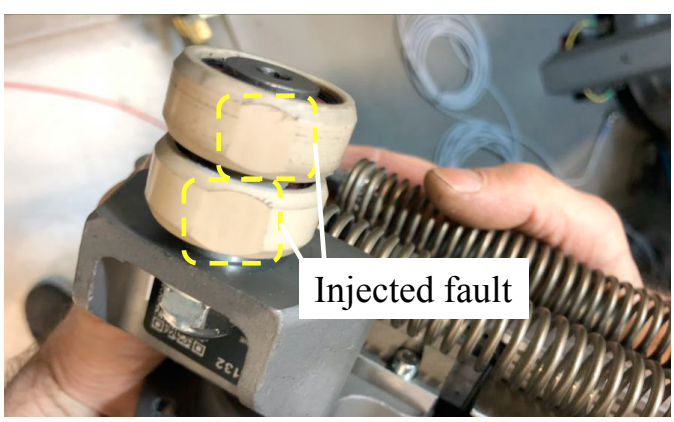

Fig. 5. Fault injection of posterior pliers bearings.

The blow molding machine operates at a set of production rates. We performed experiments at 1800 rph (revolutions per hour), where each test lasts about 3 min. The tests were performed both with all healthy pliers and a faulty one. The first preform arrives at the input pliers after 40 s, since they need to travel inside the oven. Thus, the first 40 s of the input pliers operation are without the load given by the heated preform.

As can be seen in Figure 5, the fault on the plier bearings can be interpreted as a fault on rolling balls inside a mechanical bearing. Thus, accelerometers are the best candidate sensor to monitor this specific kind of fault, see Randall (2011).

2.3 Sensors and data acquisition

We employed a single axis Hansford HS-170S piezoelectric accelerometer to measure the vibrations produced by the pliers during their operation. The accelerometer sense over the Z axis, which is the one orthogonal to the rotation axis of the pliers bearings. Since the pliers rotate, it was necessary to insert the accelerometer on the fixed structure that supports the pliers mechanics, see Figure 6. The accelerometers data are then acquired at 12.8 kHz using a NI CompactDAQ hardware.

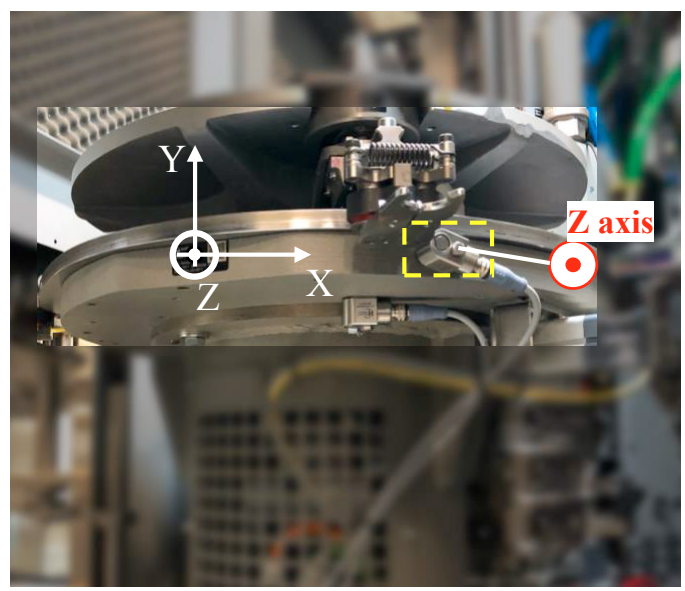

Fig. 6. Considered accelerometer over the Z axis and its positioning on the pliers structure.

The blow molding machine is able to store variables related to the motors that actuate the input/output pliers and the carousel. Specifically, it is possible to measure the following motor-related variables: (i) quadrature current, proportional to their torque; (ii) reference and measured positions; (iii) temperature.

Furthermore, a *binary indicator signal* $i(t)$ is present, that changes logical status (from 0 to 1) when a plier passes in front of a IR sensor, where t is the time index. Thus, there are 4 impulses of this indicator signal for each complete round of the input/output pliers. These machine-related signals are sampled sampled at 1 kHz.

Due to the fact that the accelerometers and the machine-related signals are sampled with different sampling frequencies, a synchronisation signal has been devised to synchronize the accelerometer and motors measurements.

3. FAULT DETECTION OF GRIPPING PLIERS

3.1 Rationale of the proposed approach

The accelerometer signals $v(t)$ can be divided into segments relying on the indicator signal $i(t)$. Each segment contains the data between two consecutive impulses in $i(t)$. Each complete round of the pliers is thus divided into four segments, that correspond to the four "working quadrants" of the gripping plier mechanism, see Figure 7.

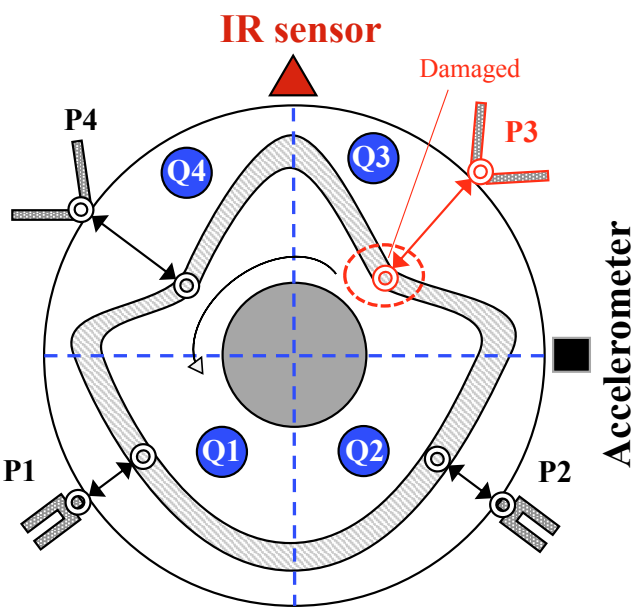

Fig. 7. Schematic of the pliers mechanism. The plier **P3** is supposed to have damaged posterior bearings.

Suppose that the damaged plier is the third one (**P3**). The bearings of the damaged plier are in close contact with the inner race of the cam where the springs of the damaged plier are stretched and its arms are open. This happens in the in the **Q3** and **Q4** quadrants. So, we expect the accelerometer measurements to be sensitive to the fault in these operating conditions.

The main idea behind the fault detection algorithm is to *consider the entire gripping pliers machinery as like as a rolling bearing structure*. The analogies between these two mechanical systems are:

- the *posterior bearings* that support the pliers are thought as a *ball* inside a rolling bearing;
- the *inner race of mechanical cam* of the pliers is thought as the inner race of the bearing;
- the *outer race of mechanical cam* of the pliers is thought as the outer race of the bearing.

Using this abstraction, the accelerometer signals are processed with techniques inspired from bearing fault diagnosis.

Remark 1. As in standard bearing diagnosis, the accelerometer data are relative to a constant rotation speed.

3.2 Fault detection algorithm

Inspired from bearing diagnosis, see Randall and Antoni (2011), the proposed algorithm for posterior bearings fault detection in input gripping pliers involves the following steps: (i) filtering the raw accelerometer data; (ii) envelope analysis; (iii) computation of fault indicators.

Data filtering As a first processing step, it is often useful to bandpass-filter the raw vibration signal, in order to enhance the fault symptoms with respect to background noise and normal operational vibrations. The Spectral Kurtosis (SK) provides a mean to determine which frequency bands contain a signal of "highest impulsiveness". These impulsive behaviours are supposed to be originated from a fault. The SK algorithm divides the spectrogram of the signal in frequency bands. For each of these frequency bands, the kurtosis with respect to time is computed. The result is a kurtosis as function of the frequency. The kurtogram plot allows to evaluate the kurtosis for different frequencies and frequency resolutions (length of the frequency window considered for the computation). The kurtogram is used to select the frequency band $[f_c - b_f, f_c + b_f]$ for filtering the raw vibration signal $v(t)$ into its filtered version $r(t)$.

Envelope computation A consolidated technique is that of envelope analysis, where the signal is amplitude demodulated to form the envelope $e(t)$, that can be more suitable for diagnostic purposes. In standard bearing analysis, the spectrum of the envelope is computed to look for specific fault frequencies. In our case, time-domain indicators are more useful since, due to the low rotation speed, it is hard to distinguish frequency components sensitive to the fault.

Fault indicators extraction We propose two indicators to monitor the posterior bearings of the pliers:

(1) the kurtosis values K of the envelope signal $e(t)$;
(2) the Root Mean Square (RMS) value R of $e(t)$.

The steps for computing the indicators are summarized in Algorithm 1. Then, fault detection is achieved by comparing one or more of the indicators with specified thresholds defined on healthy data.

Algorithm 1 Fault indicators for gripping pliers

```
function COMPUTE FAULT INDICATORS(v(t), f_c, b_f)
    r(t) ← Filter the signal v(t) in [f_c − b_f, f_c + b_f] Hz
    e(t) ← Compute the envelope signal of r(t)
    K ← Extract the Kurtosis of e(t)
    R ← Extract the RMS of e(t)
    return K, R
end function
```

4. EXPERIMENTAL RESULTS

The experimental campaign, as described in Section 2.2, is conducted only on the input gripping pliers. Figure 8 represents the first 40 s of healthy and faulty vibration signals. Although a difference is already visible on raw data, the proposed processing steps allow to enhance the diagnostic capabilities of the extracted indicators.

To this end, the raw signal $v(t)$ is bandpass filtered after bandwith selection with the kurtogram method. Figure

9 depicts the kurtogram of a faulty signal, where the optimal bandwith with $f_c = 1533\,\text{Hz}$ and $b_f = 133\,\text{Hz}$ is highlighted.

Figure 10 depicts the computed envelope $e(t)$ of the filtered vibration signal $r(t)$. Based on this, the kurtosis and RMS indicators are computed on two healthy experiments (test **H1** and test **H2**) and a faulty one (test **F**). The results, summarized in Table 1, indicate that the kurtosis is particulary sensitive to the fault, with a percentage variation of about 1617% between healthy and faulty tests. This variation is computed (both for K and R) between the average value of the indicators from the two healthy tests, and the indicator from the faulty test.

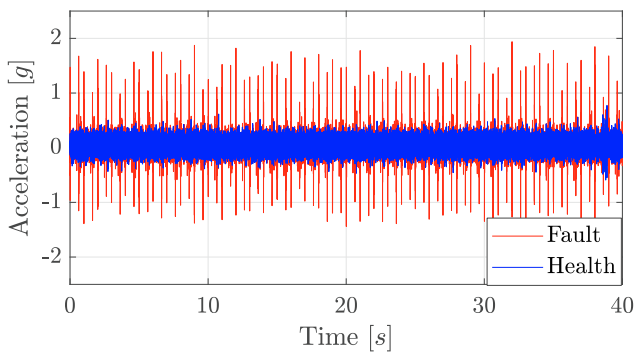

Fig. 8. Example of healthy and faulty vibration signals.

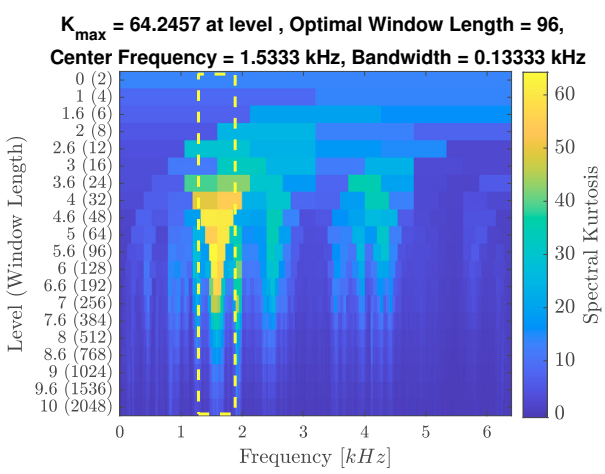

Fig. 9. Kurtogram on faulty data, with indication of the best filtering bandwith.

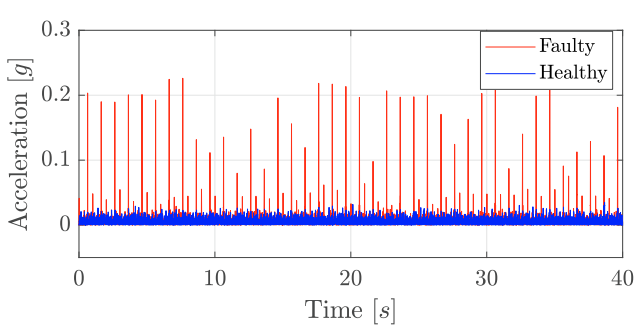

Fig. 10. Envelope of healthy and faulty vibration signals.

To better assess the validity of the proposed rationale, we selected the segments of data over one full round of the pliers, for one healthy and one faulty test. These segments were aligned over a common time axis for visualization purposes in Figure 11.

Table 1. Kurtosis and RMS of $e(t)$

	H1	H2	F	% variation
Kurtosis	6.1	5.7	101.3	+1617%
RMS	0.0075	0.0075	0.0165	+120%

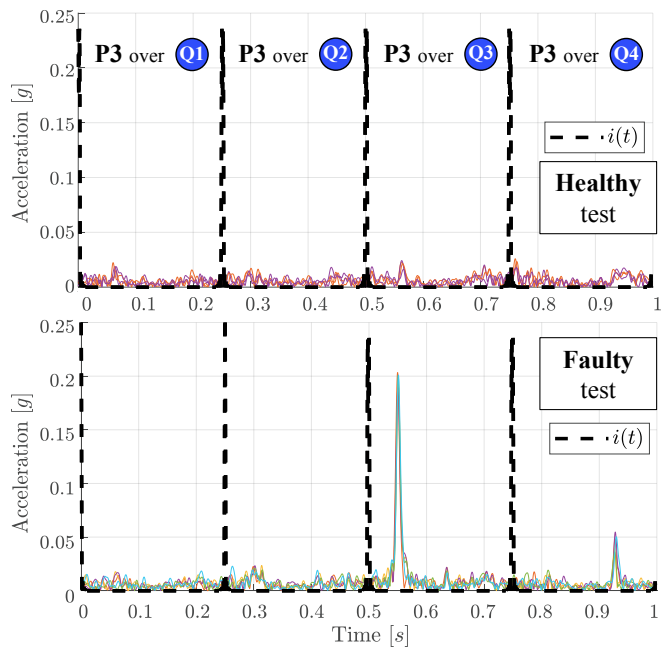

Fig. 11. Overlapped portions of data for each full round of the pliers. The indicator signal $i(t)$ groups the data into the four operating quadrant of the pliers. The passages of the faulty plier **P3** over the quadrants are showed.

First, it can be noticed that the envelope signal presents a very high repeatability. Second, the faulty envelope clearly presents fault symptoms when the damaged plier **P3** passes in the quadrants **Q3** and **Q4**. We detect higher spikes when **P3** steps over **Q3** since the accelerometer is placed closer to **Q3**. When **P3** steps over **Q4**, we detect a lower spike.

Thus, a further possibility would be to compute the kurtosis or the RMS indicators *only in the quadrants* **Q3** or **Q4**, i.e. where the springs stretches and fault is more detectable. Figure 12 shows the boxplots of RMS value of the signal portions depicted in Figure 11, in each one of the four quadrants. The plot suggests the same conclusions of Figure 11, i.e. the fault is mainly detectable in **Q3**, due to the proximity of the accelerometer to the regions of the plier mechanics that are most sensible to the fault.

Remark 2. Fault isolation, that is, to understand which plier is faulty, can be accomplished by an additional sensor able to differentiate the passage of one plier with respect to the others, e.g. by generating an impulsive signal with a different pulse length for one of the pliers.

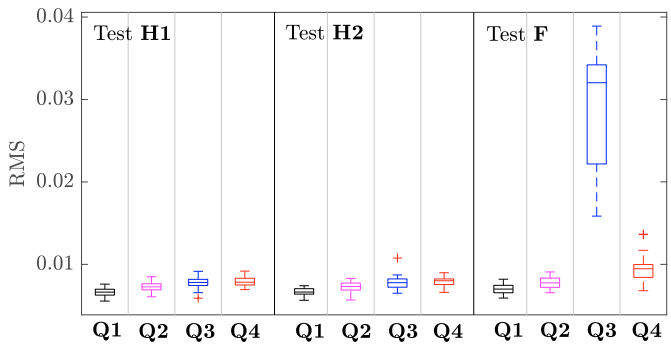

Fig. 12. Boxplots of the RMS of the envelope signal over each quadrant.

5. CONCLUSIONS

In this paper, we presented a signal-based approach for detecting the fault of the posterior bearings in an input plier mechanism for a blow molding machine in a bottling system. The approach employs accelerometers data, processed with a workflow inspired by the diagnostic of mechanical bearings. Experimental data validated the effectiveness of the fault detection method. Future work will be devoted to test more extensively the approach, along with the accomplishment of the fault isolation task.

REFERENCES

Castro, F. and Araujo, F. (2012). Proposal for oee (overall equipment effectiveness) indicator deployment in a beverage plant. *Brazilian Journal of Operations & Production Management*, 9, 71–84. doi:10.4322/bjopm.2013.006.

Ding, S.X. (2013). *Model-based fault diagnosis techniques: design schemes, algorithms, and tools, 2nd ed.* Springer Science & Business Media. doi:10.1007/978-1-4471-4799-2.

Lei, Y., Yang, B., Jiang, X., Jia, F., Li, N., and Nandi, A.K. (2020). Applications of machine learning to machine fault diagnosis: A review and roadmap. *Mechanical Systems and Signal Processing*, 138, 106587. doi:10.1016/j.ymssp.2019.106587.

Mazzoleni, M., Previdi, F., Scandella, M., and Pispola, G. (2019). Experimental development of a health monitoring method for electro-mechanical actuators of flight control primary surfaces in more electric aircrafts. *IEEE Access*, 7, 153618–153634. doi:10.1109/ACCESS.2019.2948781.

Mazzoleni, M., Scandella, M., Maccarana, Y., Previdi, F., Pispola, G., and Porzi, N. (2018). Condition monitoring of electro-mechanical actuators for aerospace using batch change detection algorithms. In *2018 IEEE Conference on Control Technology and Applications (CCTA)*, 1747–1752. doi:10.1109/CCTA.2018.8511334.

Mazzoleni, M., Rito, G.D., and Previdi, F. (2021). *Electro-Mechanical Actuators for the More Electric Aircraft.* Springer International Publishing. doi:10.1007/978-3-030-61799-8.

Papadopoulos, H. and Heavey, C. (1996). Queueing theory in manufacturing systems analysis and design: A classification of models for production and transfer lines. *European Journal of Operational Research*, 92(1), 1 – 27. doi:10.1016/0377-2217(95)00378-9.

Randall, R.B. and Antoni, J. (2011). Rolling element bearing diagnostics - a tutorial. *Mechanical Systems and Signal Processing*, 25(2), 485 – 520. doi:10.1016/j.ymssp.2010.07.017.

Randall, R.B. (2011). *Vibration-based condition monitoring: industrial, aerospace and automotive applications.* John Wiley & Sons.

Renganathan, K. and Bhaskar, V. (2013). Modeling, analysis and performance evaluation for fault diagnosis and fault tolerant control in bottle-filling plant modeled using hybrid petri nets. *Applied Mathematical Modelling*, 37(7), 4842 – 4859. doi:10.1016/j.apm.2012.07.059.

Struss, P. and Ertl, B. (2009). Post-mortem diagnosis of bottling plants based on recorded data. *7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes (SAFEPROCESS)*, 42(8), 1330 – 1335. doi:10.3182/20090630-4-ES-2003.00216. 7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes.

Troupis, D., Manesis, S., Koussoulas, N.T., and Chronopoulos, T. (1995). Computer integrated monitoring, fault identification and control for a bottling line. In *IAS '95. Conference Record of the 1995 IEEE Industry Applications Conference Thirtieth IAS Annual Meeting*, volume 2, 1549–1556 vol.2. doi:10.1109/IAS.1995.530488.

Tsarouhas, P. (2012). Evaluation of overall equipment effectiveness in the beverage industry: A case study. *International Journal of Production Research - INT J PROD RES*, 51, 1–9. doi:10.1080/00207543.2011.653014.

Valceschini, N., Mazzoleni, M., and Previdi, F. (2021). Inertial load classification of low-cost electro-mechanical systems under dataset shift with fast end of line testing. *Engineering Applications of Artificial Intelligence*, 105, 104446. doi:10.1016/j.engappai.2021.104446.

Varga, A. (2017). Solving fault diagnosis problems. *Studies in Systems, Decision and Control, 1st ed.; Springer International Publishing: Berlin, Germany.* doi:10.1007/978-3-319-51559-5.

Voigt, T., Flad, S., and Struss, P. (2015). Model-based fault localization in bottling plants. *Advanced Engineering Informatics*, 29(1), 101 – 114. doi:10.1016/j.aei.2014.09.007.