Long-term vibration monitoring of induction motors in the food industry with low-cost MEMS accelerometers

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Abstract

Many production lines in the food industry, that run continuously 24 hours per day, are nowadays equipped with induction motors to drive machines to process raw materials to become final products. As the motor function in the production lines is vital, the failure of the motor can thus interrupt the production process that eventually leads to economic losses, i.e. higher production cost. The statistical analysis on the maintenance record of a specific production line conducted in this study confirms that induction motor breakdowns are the major contributors of the unplanned production downtimes. Furthermore, this case study also shows that the common failure mode of the induction motors is due to the rolling element bearing faults, which is in-line with the findings of many authors in the literature. The main interest of the production line owner is how to minimize the unplanned downtimes such that the productivity can be maintained or increased, and at the same time, the production cost is minimized. In this paper, we present a testimonial story of a setting-up a vibration monitoring system to continuously monitor the condition of motors for the first time in a real production line with low-cost MEMS accelerometers available on the market. Some technical challenges and the state-of-the-art techniques used to compute health indicators from the measured raw vibration signals are presented in this paper. The installed vibration monitoring system has successfully identified a damaged bearing in one of the monitored motors. This finding was also independently validated by a maintenance service company.

1. Introduction

Operations cost efficiency enhancement is the primary decision driver of manufacturing enterprises, in order to stay economically competitive [1]. It not only refers to reducing resource (material, energy, machine and labour) utilization per unit of manufacturing process output, and improving product quality and yield per unit of input but also includes reducing unplanned downtimes or delays of the production process due to technical issues (machine breakdown, unavailable material, blockage of a line). Conventionally, manufacturers tend to ignore a full exploration of the enormous power of data, although these data have huge potential to help increase their operations cost efficiency [2]. The production-related data generated on the shop floor is various, such as production logs, power consumption, maintenance registers, machine performance indicators, labour shifts, material availability, and storage status. A majority of manufacturing enterprises either do not gather these data, or have fragmented data, or simply store these data without any further management and analytics.

With the emerging industrial transition toward Industry 4.0, the penetration of Internet-of-Things (IoT) technologies into manufacturing industry (industrial IoT, or IIoT) enables collecting these various data in a cheaper and more flexible manner [3], hereby unlocking the enormous potential of big data technologies applied to production lines. In this paper, we discuss our experience in assisting a food manufacturing company that runs its production lines 24 hours per day in the transition toward Industry 4.0. This company has a number of production lines to manufacture different types of food. The key performance indicator (KPI) set by the company that need to be achieved within this project is an improved operation cost efficiency and productivity.

The production lines availability is one of the other important aspects that influence the operation cost efficiency and productivity. Currently, the *preventive maintenance* is applied to the production lines to maintain the availability, where the production lines have to be stopped in every pre-determined maintenance window (e.g. every few weeks). To reach the KPI, the maintenance strategy, therefore, needs to be changed from the *preventive maintenance* to the *condition-based maintenance (CBM) /Predictive Maintenance (PdM)* strategy. The **first critical step** to successfully implement the CBM/PdM strategy is to identify critical assets that have a significant impact on the business. Here, the asset criticality is determined by the duration of production downtimes caused by the failure of a certain asset. The longer the production downtime is, the more critical the asset will be.

Since the beginning of the project, it was not entirely clear yet what production lines/sub-production lines or machines that can be categorised as critical assets. To identify critical assets in an objective manner, the maintenance record and production data of a pilot production plant for more than 6 years (from April 2011 to November 2017) were analysed. The analysis revealed that most of the downtimes in the production plant are caused by the failures of AC electric motors located at different production lines. Further analysis also showed that the majority of the AC electric motor failures is caused by the mechanical damages on the rolling element bearings.

Once the critical assets have been identified, the **second step** is to determine which technologies necessary to monitor the health condition of the critical assets. Vibration based condition monitoring is a well-established approach that has been employed by industries for many years in their maintenance program of rolling element bearings [4]. The common practice of this approach is that, vibration measurements are periodically recorded using portable vibration sensors (i.e. accelerometers) and measurement signals are analysed by an expert to interpret the bearing condition. However, this common practice can lead to serious misinterpretation, where rapidly growing faults, that might occur in rolling element bearings, could be missed. In contrast, a continuous condition monitoring approach offers a more optimal solution in which the bearing condition is continuously tracked. This way total failures can be anticipated in advance thus allowing optimal maintenance action. Despite its advantages, the continuous monitoring program is however not well adopted by industry because of high investment cost, where sensor cost is a major factor. To remedy this gap, cost-effective accelerometers are therefore needed.

The remainder of this paper is organised as follows. Section 2 discusses the market survey for low-cost accelerometers suitable for bearing condition monitoring purposes. Section 3 describes the architecture of the continuous monitoring system installed in a production line. Section 4 discusses the analysis results of the data acquired by the installed monitoring system. Section 5 presents the conclusions drawn from the analysis and proposes a future work.

2. Sensor Selection and Deployment

The high investment cost is one of the bottlenecks for adopting continuous condition-based maintenance strategies in the industry. A major part of these costs is introduced by the sensors. Advancements in the field of MEMS accelerometers have enabled opportunities for low-cost alternatives while maintaining basic-performance requirements for vibration-based condition monitoring purposes.

MEMS accelerometers offer many attractive attributes. They combine the economic benefit with, for example, a compact, a high sensitivity, a good resistance to shocks and acceptable stability over a wide range of temperatures. In the previous study [5], a market survey was carried out and it was concluded that the only MEMS accelerometers available on the market suitable for vibration-based condition monitoring (in particular for bearing faults monitoring) are the ones from Analog Devices, ADXL001-70/ ADXL001-250. The main criteria for selecting such sensor models are because of *i*) the high dynamic range and *ii*) the wide frequency range properties. However, the noise performance over higher frequency ranges of the selected sensor models is relatively low, *i.e.* higher noise density level, which is about **4000 µg/√Hz**.

Recently, the market study has been updated as summarised in Figure 1. It turns out that Analog Devices has released the new generations of MEMS accelerometers for more than one year, namely ADXL1001/ADXL1002 having ultra-low noise density level, which is about **25 µg/√Hz**. These ultra-low noise sensor models are the successor of ADXL001-70/ADXL001-250. Despite the fact that the noise density level of the successors is much lower than that of the predecessors, other potential limitations of the low-cost ADXL1001/ADXL1002 MEMS accelerometers such as the long-term signal drift, bias offset and overall robustness of the sensor to industrial environments, are not clear yet.

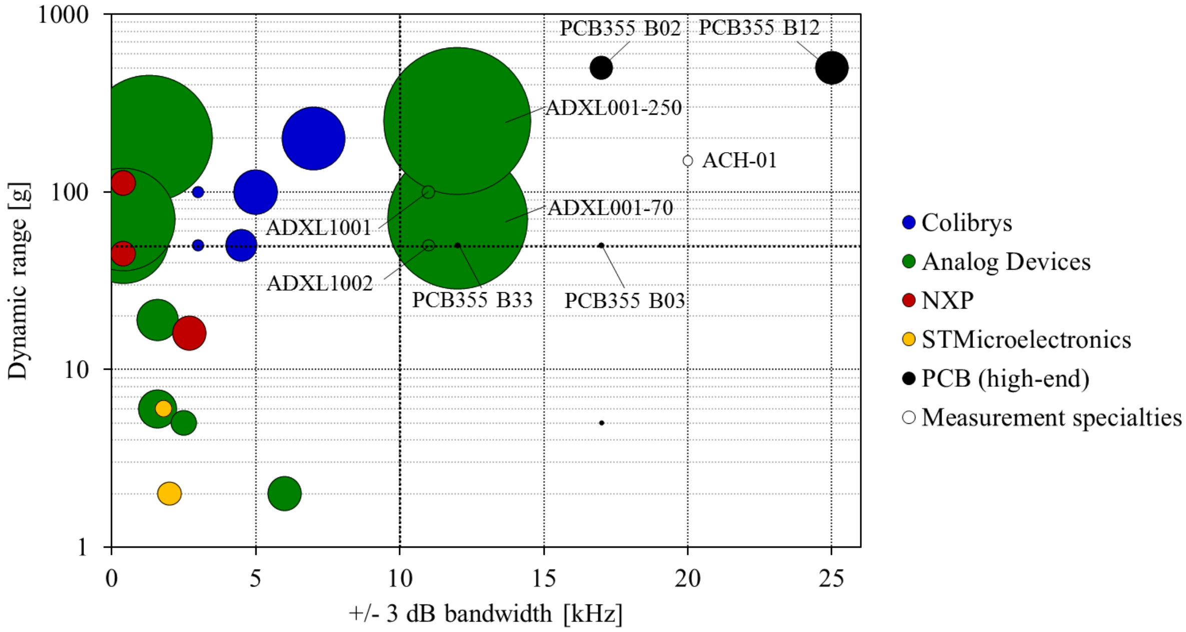


Figure 1: The market overview of analogue MEMS accelerometers updated version of [5]. The dashed lines indicate the minimum requirements set for condition monitoring applications. The diameter of the circles indicates the noise density as specified in the datasheets.

Proper hardware solutions were exploited to cope with the inherent limitations of the low-cost MEMS accelerometer that can affect the monitoring performance. To this end, a printed circuit board (PCB) and a tailored-packaging have been designed and produced. Figure 2 schematically illustrates the sensor deployment process to protect the MEMS sensor and enhance its overall robustness. To preserve the frequency range of the MEMS accelerometer, the packaging should be designed with care. For this purpose, a design criterion for the packaging was imposed, namely, the first packaging resonance frequency should be higher than the maximum frequency range of interest, i.e. 10 kHz. The flowchart of the packaging design is shown in Figure 3.

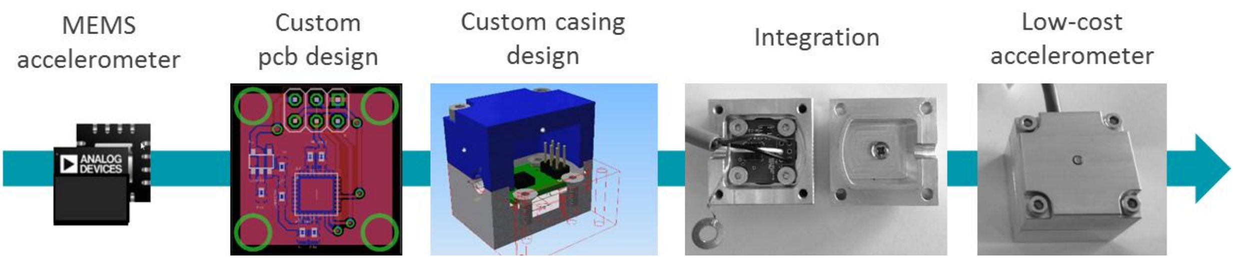


Figure 2: Sensor integration and packaging process.

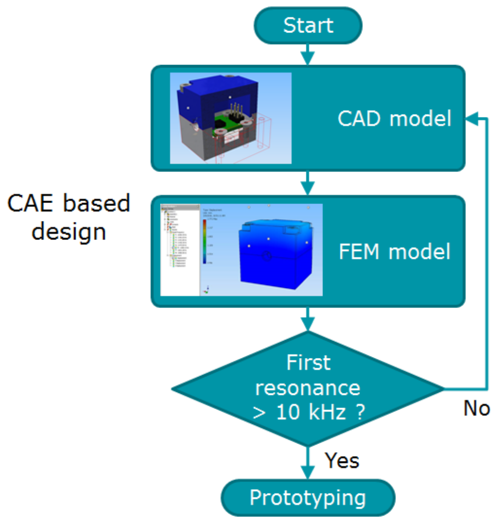


Figure 3: Packaging design flowchart.

3. The Continuous Monitoring System Architecture and The Installation in A Production Line

The asset criticality analysis, as discussed in Section 1, has guided us to consider 4 electric motors which are located in different locations. Hence, four of the selected ultra-low noise sensor model (ADXL1002) have been packaged according to the sensor deployment flow described in Section 2.

Figure 4 illustrates the architecture of the monitoring system, in which each vibration sensor is installed on an individual motor. Each sensor is oriented such that the measuring axis in parallel with the horizontal axis and radial axis of each motor. Note that each sensor is powered by 5 VDC power supply. Sensor #1 and #2 are both installed on an extrusion press in a regular industrial environment, while sensor #3 and #4 are installed on a ventilator and belt motor subject to harsh environmental conditions with the temperature variations between 20 and 120°C and the humidity up to 90%. The latter stressed conditions have a major impact on the lifetime of the motor bearings and are an ideal industrial use case for this study.

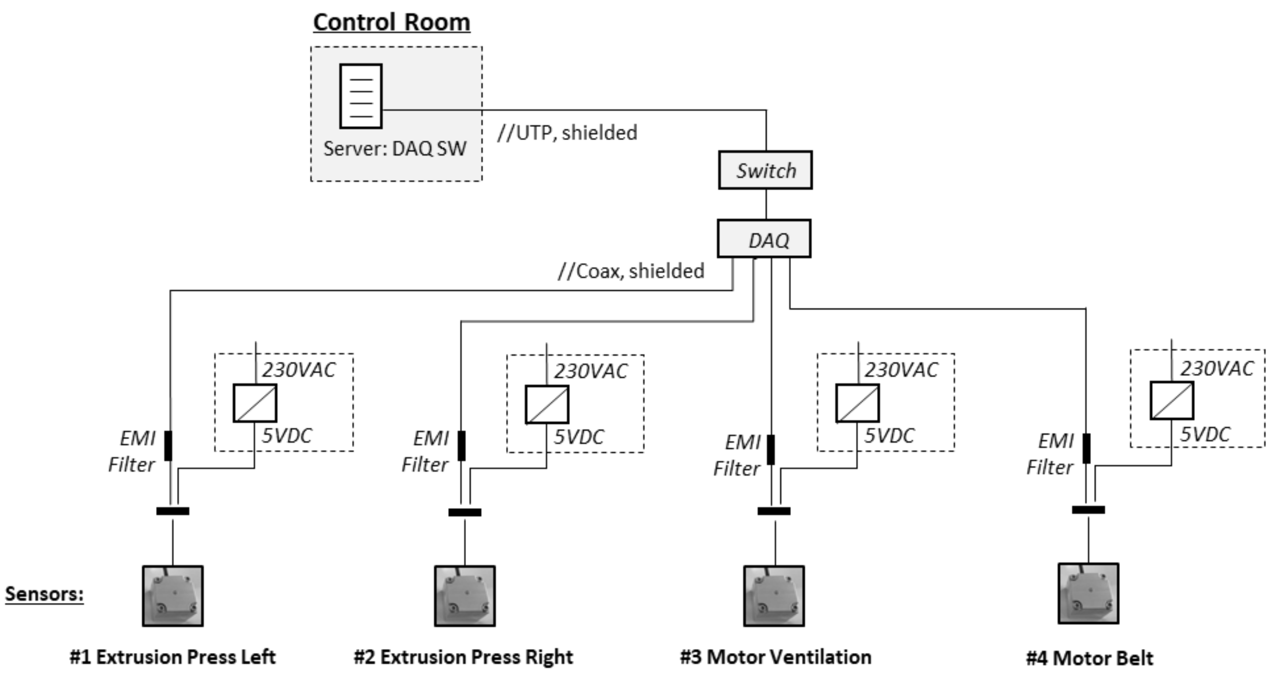


Figure 4: Architecture of the monitoring system installed in a production line.

Each sensor is individually connected to a four-channel data acquisition device (NI CDAQ9191) sampled at a high frequency of 50 kHz. The digital data from the data acquisition device is transferred to a server via an ethernet cable. On the server, a custom data recording program shown in Figure 6, which can be scheduled along the working hours, is run, which stores every half hour a few seconds of data. This monitoring system has been successfully running and generating a dataset of almost one year of production data.

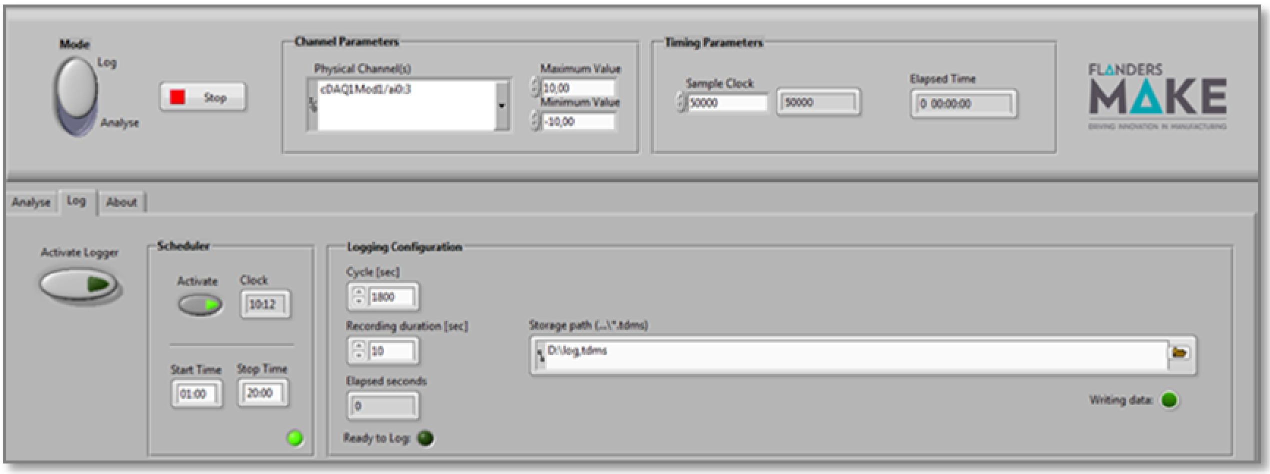


Figure 5: Custom data recording program.

The two sensors installed in the regular industrial environment are still in operation until now. In contrast, after more than one month since the installation, the two sensors installed in the harsh environmental conditions showed an anomaly behaviour, where the DC values of the raw signals have dropped to values around zero. The comparison of the raw signals of a functional and failing sensor is shown in Figure 6. It is not clear yet the reason for the sensor failure. But it seems that one of the electronic components used in the sensor packaging is vulnerable to a long time high temperature.

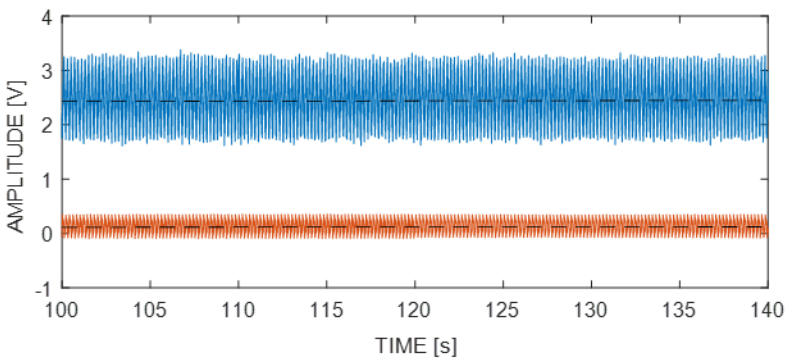


Figure 6: Raw sensor data of a functional (top) and failing (bottom) sensor, sampling at 50 kHz.

4. Data Analysis

Batch data acquisition Sensor data are acquired in batches: in a standard operating mode, a batch is recorded every 30 minutes. If necessary (e.g., if data analysis indicates imminent failure), the acquisition period can be gradually reduced to ensure up-to-date information for decision-making. The length of a batch depends on the rotational speed of the motor: for reliable analysis, a batch should contain a sufficient number of full revolutions. The rotational speed of the monitored motors while executing a typical production order ranges from 1400 to 1500 RPM (approximately 25 Hz), therefore we set the batch length to three seconds. Thus, one sensor generates at least 57 megabytes of uncompressed raw vibration data per day.

Computing health indicators For each monitored motor and each batch, we compute several bearing health indicators, referred to as *features*. Figure 7 illustrates the feature computation algorithm. It requires three inputs: bearing fault frequencies, the rotational speed of the motor shaft, and the raw vibration signal. The required bearing fault frequencies include the bearing defect frequency (BDF), and the inner & outer ball pass frequencies (BPFI & BPFO), and the ball spin frequency (BSF) for the drive and non-drive ends; their values typically can be found in the manufacturer's catalogue. The shaft speed can either be directly read from the motor controller interface (PLC) or estimated from the vibration data; in this work, we use the latter method. To filter out non-production situations (e.g., maintenance, cleaning, holidays, etc.), we skip the batches where the rotational speed is much lower than the typical values of 1400-1500 RPM; we set the filter threshold to 600 RPM.

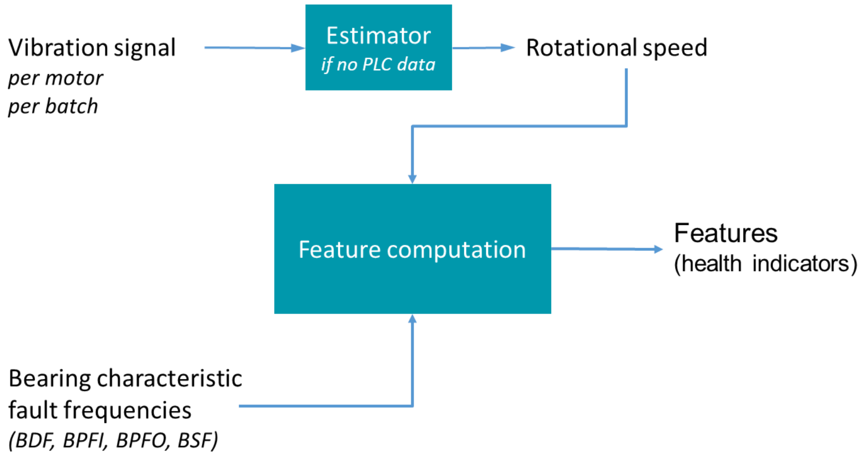


Figure 7: Inputs and steps of the feature computation algorithm.

From a high-level perspective, the main steps of the algorithm are (1) centering the vibration signal, (2) estimating its envelope spectrum, and (3) informally, matching the spectral peaks with the expected fault frequencies: the closer the match, the higher the feature value and hence, the likelihood of a bearing failure. Figure 8 illustrates the third step: the bearing monitored by *Sensor#2* is substantially more likely to fail than the one monitored by *Sensor#1*. For the detailed description of the algorithm and its options, we refer the reader to Ompusunggu *et al.* [5].

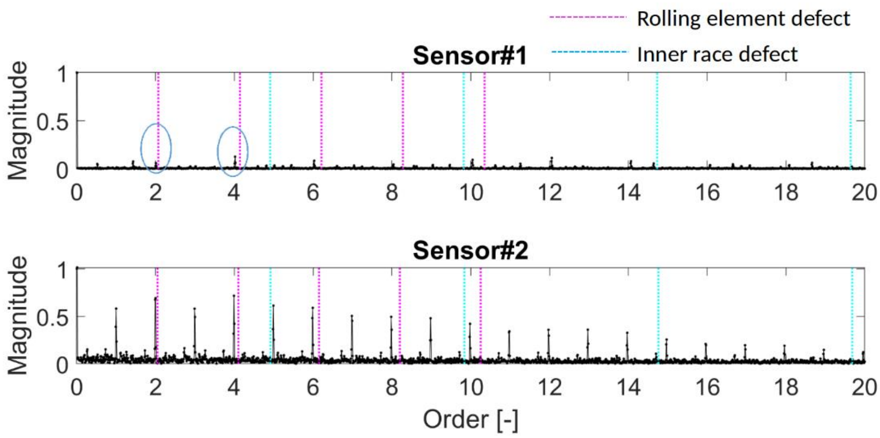
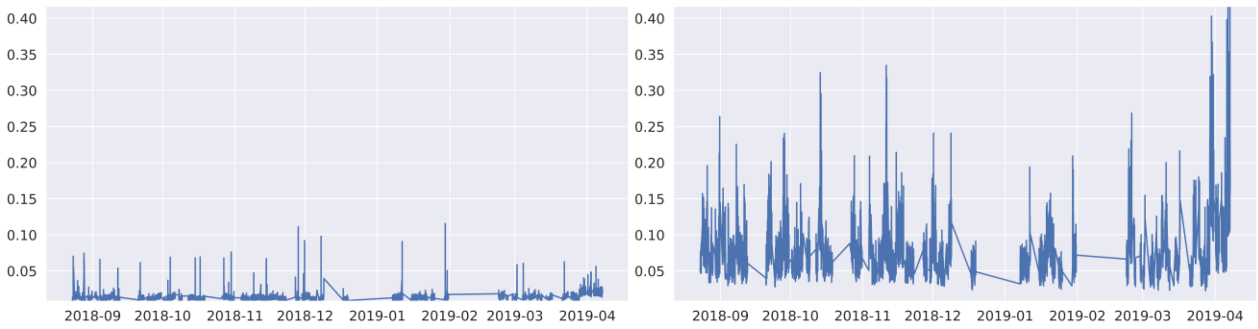


Figure 8: Final step of feature computation: matching *envelope spectral* peaks with bearing fault frequencies. Close matches for *Sensor#2* likely indicate bearing fault.

The algorithm computes 10 features in total: 8 features for each fault frequency listed above, one feature for the shaft, and an aggregate *global* feature. This enables a coarse-grained overview as well as fine-grained analyses. Figure 9 shows the evolution of the global feature over time for the two motors shown in Figure 8, indicating the stable condition of the first motor and the gradual increase of the failure likelihood of the second motor. These findings have been confirmed by an external audit.



(a) Sensor#1 (b) Sensor#2

Figure 9: Evolution of the global bearing health indicator for two motors over eight months (missing values correspond to non-production periods, e.g., maintenance or holidays).

Remaining data analysis challenges include *accounting for operational context* and *calibration*. Relevant contextual data (such as the shaft speed, load, ambient temperature, raw material, etc.) can be read from PLCs and various manufacturing systems, e.g., SCADA or MES. Accounting for these data will reduce the influence of external factors and mitigate spurious feature value fluctuations seen in Figure 9. Calibration requires data from the complete lifecycle of a bearing, from installation to failure. Once such data become available, dimensionless feature values can be used to calculate interpretable health indicators, e.g., fault size or time to failure.

Implementation details The software is implemented in MATLAB with a thin Python wrapper for scripting. The implementation reads the TDMS files output by the NI acquisition device and generates CSV files that can be used directly or uploaded to a database, an IoT platform, or another data processing system.

5. Conclusions & Outlook

In this paper, we have shared our experience in assisting a food manufacturing company in setting up a continuous monitoring system in transition from the current practice *preventive maintenance* toward the condition-based maintenance/predictive maintenance. The maintenance record and production data recorded for more than 6 years have been used and analysed to objectively determine critical assets in a pilot production plant. It turns out from the analysis that AC electric motors located in different production lines are the most critical assets, where rolling element bearings are the main root causes of the motor failures.

The architecture of the monitoring system with a low-cost vibration sensor solution has been proposed and realised in the pilot production line to monitor the health condition of four selected electric motors. The monitoring system has been running successfully and acquiring vibration data, which are stored in a server. The off-line analysis has shown that one of the selected motors is already faulty. The findings have been verified independently by a third party. As a result, a maintenance action for the faulty motor has been planned and will be executed in the coming weeks.

The future work will be to further extend the framework that allows for on-line analysis and decision making.

Acknowledgements

This work was executed within the imec.icon project ELITE, a research project bringing together academic researchers and industry partners. The ELITE project was co-financed by IMEC, Flanders Make and received project support from Flanders Innovation & Entrepreneurship (VLAIO).

The work of sensor selection and deployment was executed within the VIBMON_ICON project, co-financed by Flanders Make and VLAIO.

References

[1] F. Jaehn, “*Sustainable Operations*” European Journal of Operational Research, 2016; 253, 243-264.

[2] E. Auschitzky, M. Hammer and A. Rajagopaul. “How big data can improve manufacturing,” McKinsey&Company article, July 2014, http://www.mckinsey.com/business-functions/operations/our-insights/how-big-data-can-improve-manufacturing

[3] J. Wan, S. Tang, Z. Shu, et al. "Software-Defined Industrial Internet of Things in the Context of Industry 4.0," IEEE Sensors Journal, 2016; 16(20): 7373-7380.

[4] R. B. Randall & J. Antoni. Rolling element bearing diagnostics-A tutorial. Mechanical Systems and Signal Processing, Vol. 25, p. 485–520., 2011.

[5] A. P. Ompusunggu, T. Ooijevaar, B. Kilundu, S. Devos, *Automated Bearing Fault Diagnostics with Cost-Effective Vibration Sensor*: Proceedings of the 12th World Congress on Engineering Asset Management and the 13th International Conference on Vibration Engineering and Technology of Machinery, 2019.