

Development of an advanced condition-based maintenance system for high-critical industrial fans in a foundry

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Abstract: In the recent years, manufacturing companies are investing in sensors and information systems to implement condition-based maintenance (CBM), thus pursuing the benefits of digital transformation. Nevertheless, to implement CBM as advanced digital system, significant investment should be made to gather and manage all needed data from different sources; besides, qualified human resources are required for data analytics. Given this premise, the present paper aims at describing an industrial project where an advanced CBM system for high-critical industrial fans is implemented in a foundry. Indeed, the goal is to use already available data from the extant automation and additional vibration data to develop state detection and to identify any abnormal behaviour of the assets. The evidence from the project is that: i) the vibration analysis remains an easy and cost-effective, yet well-performing way, to monitor the state and the health of machines with rotating components; ii) automatic regulation system may mask the underlying behaviour and degradation of complex assets; iii) already gathered data from extant automation are mainly focused on the process parameters and provides an aid to describe the working state of the assets, but have limited potentialities for novelty detection. Eventually, the paper envisions future development of a more integrated approach aimed at a combined elaboration of data from the extant automation and vibration data. The integrated approach is under development, hence the paper provides insights on the on-going analyses.

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Keywords: condition-based maintenance, CBM, prognostics and health management, PHM, state detection, health assessment, vibration, warning system, industrial fan, manufacturing.

1. INTRODUCTION

Manufacturing companies are undergoing radical changes dictated by the digital transformation. It offers to companies a wide spectrum of new possibilities, like the development of new business models that better fit the requirement of the market (Ulas, 2019). This transformation is based on the availability of more and more data thanks to the digital technologies that are pervading the manufacturing industry (Borangiu et al., 2019). Consequently, the greater amount of data available and the higher computational power the current devices have allow to better monitor and control what is happening at the shopfloor level of companies (Lee et al., 2016). This enables production and maintenance management to perform better than in the past by responding faster to unforeseen events that could slow down or stops the production (Negri et al., 2019). It is especially maintenance that is finding its “golden age” as a progressive evolution from the E-maintenance of the first decade of 21th century (Guillén et al., 2016) to the new concept of Smart Maintenance (Bokrantz et al., 2020). Currently, it is possible to gather

insights on machine health states through the application of advanced solutions for condition-based maintenance (CBM), collecting real-time data from the industrial assets as well as elaborating data through adequate analytics, embedded in CPS (Cyber Physical System), to support reactive or proactive actions (Gao et al., 2021).

The data sources are different and could include sensors installed on the assets, controllers like PLC (Programmable Logic Controller) and CNC (Computer Numerical Control), as well as enterprise information systems such as the MES (Manufacturing Execution System) or the ERP (Enterprise Resource Planning) (Tao et al., 2018). Additionally, relevant data for CBM purposes may also come from third parties, like outsourcing companies that are in charge of the maintenance activities (Murthy et al., 2015). Overall, the collection of relevant variables for CBM could be expensive for various reasons, either technical (specific sensors to be installed, cloud computing power to be paid) and organizational (workforce allocated to the monitoring activities or persons to train for the data analytics activity). Therefore, the implementation of advanced CBM capabilities should be tested beforehand with

available data within the company or with the introduction of general-purpose sensors in order to guarantee cost-effective proof of concepts (Ahmad & Kamaruddin, 2012).

This work describes the development of an advanced CBM system for high-critical industrial fans. This multi-year project is performed in collaboration with a foundry realizing semi-finished products for the automotive market. In this project, the developed solutions rely both on already available data from the SCADA (Supervisory Control And Data Acquisition) and acceleration data due to a newly installed accelerometers system. The two solutions are initially developed separately, to understand which one better fits for the project goal. Based on the evidence gathered from the two solutions in a separate way, some more insights on the possible integration of both data, and related analytics, are proposed; it envisions the future development of a more integrated warning system.

The paper is structured as follows. Section 2 describes the case study, with details on the industrial fans (target of the CBM), the process they must serve, and the adopted methodology. Section 3 illustrates the FMECA (Failure Modes, Effects and Criticality Analysis) identifying the most critical failure modes. Section 4 deals with the vibration analysis performed on data coming from the accelerometers. Section 5 proposes the exploratory analysis of the already available data from SCADA. Section 6 describes the ongoing analyses, in order to envision the future development of an integrated warning system. Eventually, Section 7 summarises the results and draws some conclusions on the project experience.

2. DESCRIPTION OF THE CASE STUDY

The case under analysis is the one of a foundry in the northern part of Italy. The foundry produces semi-finished products for the automotive sector. Figure 1 shows the phases of the process according to the ASME (American Standards of Mechanical Engineers) graphic symbols for process flow diagrams.

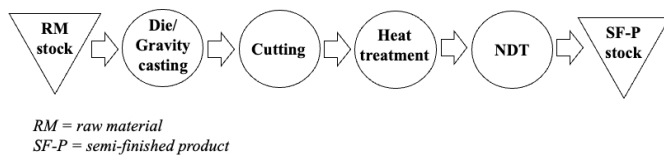


Figure 1. Process flow of the foundry.

The process represented in Figure 1 is the primary process of the foundry, but there are ancillary processes, with relative systems/assets, that enable the correct functioning of the primary process. Amongst those ancillary processes, there is the flue gases filtering to remove contaminants from output air in order to guarantee safe workplace on the shopfloor as well as compliance with environmental regulations. The flue gases filtering relates to two main areas:

- Hot flue gases filtering for the die casting;
- Cold flue gases filtering for the gravity casting.

The two filtering processes are served by two assets. Their characteristics are the following, respectively: an industrial fan of 170000 m³/h, 600 bags of polyester type and a power of 315 kW, and an industrial fan of capacity 90000 m³/h, 350 bags of

aramid type and a power of 110 kW. Figure 2 shows a schema illustrating the structure of an industrial fan.

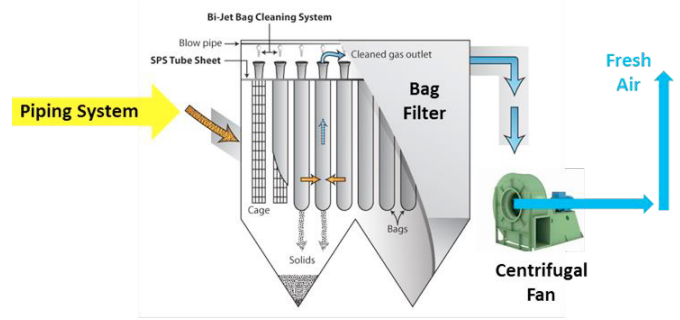


Figure 2. Functioning schema of the industrial fan.

The goal of the project is to develop an advanced CBM system capable to promptly notify about an abnormal behaviour of the industrial fans. As the industrial fans guarantee a safe working environment, the prompt notification is essential. If they fail, the entire plant should be stopped in order to restore adequate working conditions. Hence, the industrial fans are high-critical assets since they are operationally risky and do not have spare assets in stand-by that could operate in case of failure.

2.1 Project methodology

The methodology followed during the project is inspired by (Cattaneo et al., 2021), based on PHM (Prognostics and Health Management), and is reported in Figure 3.

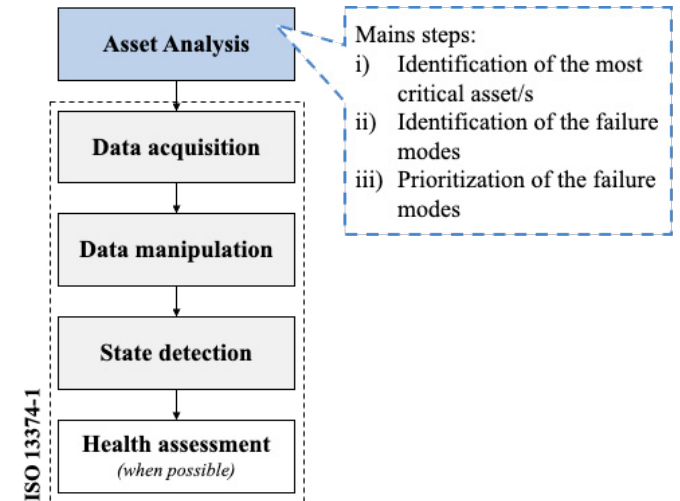


Figure 3. PHM-inspired methodology in the project.

In addition to the traditional functional blocks considered in the ISO 13374-1 (equivalently, in the OSA-CBM, Open System Architecture for Condition Based Maintenance, by MIMOSA – <https://www.mimosa.org/mimosa-osa-cbm/>), the methodology includes a first functional block called Asset Analysis that focuses on the prioritization of assets and their failure modes and promotes a better understanding of the asset functioning and characteristics. The Asset Analysis is described in Section 3.

3. ANALYSIS OF THE INDUSTRIAL FANS

To prioritise the failure modes, it is important to understand the physical decomposition of the industrial fan. Figure 4 reports the physical structure of the asset under analysis, limited to the first level for the sake of visualisation.

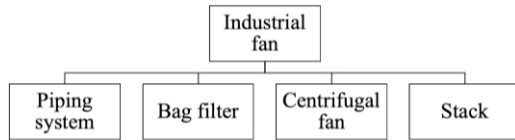


Figure 4. Physical decomposition of the industrial fan.

To prioritise the failure modes, the MAFMA (Multi-Attribute Failure Modes Analysis) by (Braglia, 2000) is employed, given that the critical asset is already identified. MAFMA is based on AHP (Analytic Hierarchy Process). In the project, the AHP criteria are the parameters of the FMECA, namely occurrence, severity, and detectability, while the alternatives are the eleven identified failure modes. The structure is represented in Figure 5.

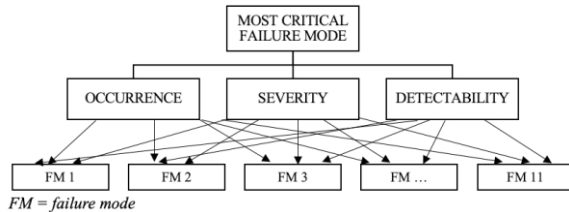


Figure 5. MAFMA applied to the project.

The three criteria (occurrence, severity, detectability) are equally weighted (0.33 each). For the alternatives evaluation, after the definition of a scale for each of the three criteria, the MAFMA was firstly filled in with data coming from the maintenance reports of the centrifugal fan and of the bag filter, later validated through an interview with three maintenance technicians and the maintenance manager. The advantages to use MAFMA, built on AHP, is that it can manage both quantitative and qualitative inputs. This is particularly useful for the detectability that is hardly measurable objectively. Table 1 shows the top-five highly ranked failure modes with the associated component and system (bag filter or centrifugal fan) of the industrial fan and their global priority value.

Despite the failure mode of the solenoid valve is the one with the highest priority, together with the maintenance manager, it was decided to monitor the engine, coupling and supports.

Table 1. Results of the application of MAFMA.

Rank	Sys.	Component	Failure mode	Priority value
1	BF	Solenoid valve	Ageing of the valve spool	12.38%
2	CF	Engine (shaft and bearings)	Overheating	10.57%
3	CF	Coupling	Deterioration of coupling slats	10.30%

Rank	Sys.	Component	Failure mode	Priority value
4	CF	Supports (ring, spacer, seal)	Overheating	10.30%
5	CF	Impeller shaft	Overheating	9.76%

BF = bag filter, CF = centrifugal fan

The decision is due to a trade-off between the costs needed to implement the solution and the opportunities subsequently reachable. Specifically, the engine, coupling and supports are really close each other; thus, the new monitoring system, to be designed, could be composed by only three accelerometers and one central unit. Thus, this solution allows to monitor the evolution of three different failure modes without much spending with respect to each of them. This was identified as cost-effective solution to further develop. Section 4 describes the vibration analysis subsequently carried out.

4. VIBRATION ANALYSIS OF CENTRIFUGAL FAN

The vibration signals are collected thanks to a new monitoring system installed on the centrifugal fan as depicted in Figure 6.

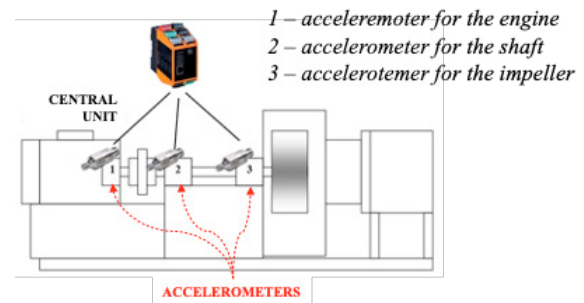


Figure 6. Vibration acquisition system.

The accelerometers are characterised by a sampling frequency of 50 kHz and are installed one per bearing.

The vibration analysis is carried out considering the ISO 10816-3 – Mechanical vibration - Evaluation of machine vibration by measurements on non-rotating parts to implement the state detection. The standard identifies specific HI (health index) thresholds, based on RMS (Root Mean Square), for machines of certain size with respect to their power. The industrial fan for the cold flue gases, whose power is of 110 kW, is considered of medium size by the standard (from 15 to 300 kW). In the remainder, the fan for the cold flue gases is used as exemplar to show the developed solution. The same has been done for the hot flue gases industrial fan. Medium-sized machines have specific values of the RMS as reported in Figure 7.

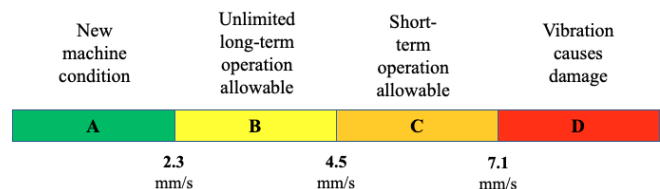


Figure 7. HI thresholds according to ISO 10816-3.

In Figure 8, it is observable the continuous monitoring of the RMS during the last week of March 2021. Each point represents the RMS value, and it is coloured to trace the

rotational speed of the shaft. It is worth noticing that the RMS barely fell over 4 that is the limit for HI of type B “Unlimited long-term operation allowable” according to Figure 7.

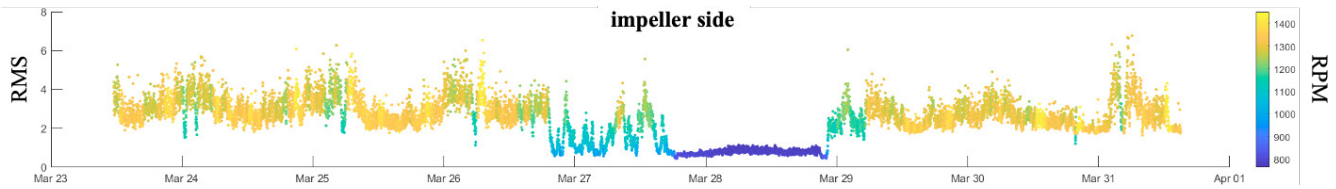


Figure 8. Continuous monitoring of RMS during the last week of March 2021; during the weekend the industrial fan is kept in active standby.

Continuing the methodology in Figure 3, the health assessment functional block could be performed by looking at the ISO 13373 – Condition Monitoring and Diagnostics of Machines – Vibration condition monitoring (specifically, part 3 and 5), integrated by the tutorial published by (Randall & Antoni, 2011). The analysis includes both frequency spectrum and envelope spectrum. However, the former suffers of some pitfalls in industrial applications since random noise and resonances could hinder the peaks due to fault, when at its early stage. Therefore, the envelope spectrum is adopted, and it was possible to identify that there was a problem, possibly a misalignment, on the outer race of the motor bearings, given

the peaks at 1x and 2x of the BPFO (Ball Pass Frequency of the Outer Race), as shown in Figure 9, with an amplitude from 2 to 10 times the one of BPFI (Ball Pass Frequency of the Inner Race).

Even though the envelope spectrum analysis suggested a damage of the outer race of the bearings on the motor side, the RMS values were still in the acceptable range. Therefore, the maintenance manager decided not to act immediately on the bearings, instead engaging the outsourcing company in charge of the maintenance service to better investigate and define the better way to proceed.

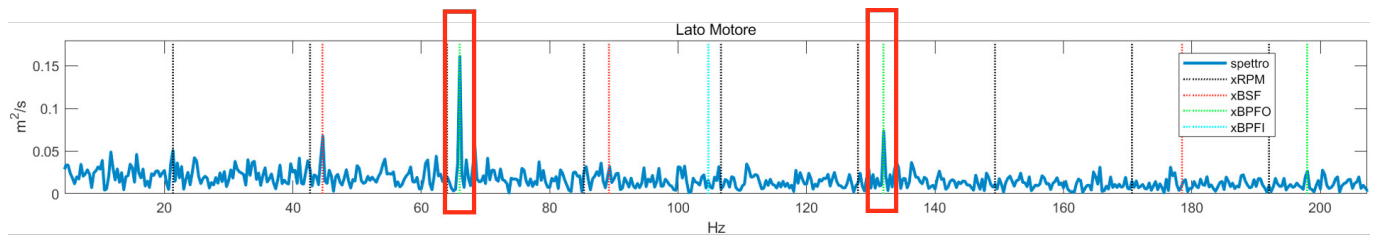


Figure 9. Analysis of the envelope spectrum on March 4th, 2021, at 15:29:59; the ratio of amplitudes at BPFO and BPFI is almost 10.

Overall, by combining the analysis of vibration signals and the predetermined HI defined by the ISO 10816-3 (Figure 7), it is possible to conclude that the vibration analysis technique provides enough information content for decision making based, at least at first sight. Nonetheless, this analysis does not provide useful insights on the overall health state of the industrial fan, but only for some specific components (bearings of the centrifugal fan) as it was any expected by design. In the next section 5, the already available data collected by the SCADA are analysed for possible further insights.

5. ANALYSIS OF DATA FROM SCADA

The data already available from the SCADA are reported in Table 2, where f_s is the sampling frequency.

Table 2. Already available data from SCADA.

Variable	Location	Unit	f_s [kHz]
Pressure	Inlet pipe	mmH2O	1
Temperature	Inlet pipe	°C	5
ΔP	Bag	mmH2O	10
Motor RPM	Inverter	RPM	10
Current	Inverter	A	1
Particulate	Chimney	mg/nm ³	5

The available data underwent firstly a pre-processing phase that was required since the sampling frequency differ between variables, as notable from the rightmost column in Table 2. The choice was to select the highest sampling frequency and re-build the signals of variables with lower f_s by adopting the LOCF (Last Observation Carried Forward) imputation.

Secondly, an explorative analysis was performed to get a first impression on the insights the data can produce. The result for the ΔP is shown in Figure 10 where the different states of the industrial fans were highlighted (on, off, transient on, transient off).

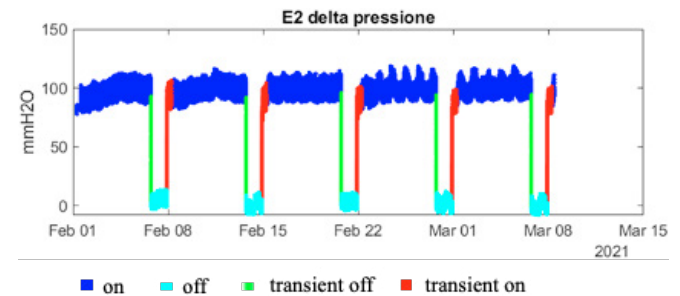


Figure 10. State analysis for the industrial fans.

Further analyses through data processing on the other variables did not show useful insights on the health state of the asset.

On the whole, the information content given by the data from the SCADA is exclusively related to the working state of the industrial fan. In fact, the collected data are mainly focused on the process parameters and not on the asset side (like it happens for vibrations). This results from different operating conditions, as discussed with the maintenance manager:

1. the workload to which the industrial fan is subjected to different changes during the week and even the day depending on the number of casting operations;
2. the industrial fan has an automatic regulation system in order to keep the same reference value for ΔP by adjusting all the other ones; however, the variation of the other signals is very limited (plots are not shown here for brevity); also, this inner control may “mask” the behaviour of the industrial fan.

Concluding, it is apparent that the analysis of process-driven variables did not show relevant results to be used for CBM purposes since the relevant information useful to the manager to take reactive actions is hidden and biased by other factors.

6. ONGOING ANALYSES FOR A FUTURE INTEGRATED ADVANCED CBM SYSTEM

Currently, several analyses are on the way, to enable building an integrated approach from SCADA and vibration data. This is done to empower the data analytics, thus, to extend the capability of data analytics from single component to asset behaviour.

Firstly, from the vibration analysis, a strange behaviour of the industrial fan, particularly, of the centrifugal fan, is detected, even if the maintenance record does not show maintenance interventions. In Figure 11, the plot of RMS versus RPM is reported. It is worth noting that the trend of the RMS may be modelled as a quadratic function with respect to the RPM with a high coefficient of determination R^2 for low RPM. However, as the RPM increases, the R^2 decreases, meaning that the function is no more able to predict accurately the RMS based on RPM. Moreover, the RMS values above RPM equal to 1240 are really scattered and present a U-shaped trend with high variability. This may be induced by some resonance effects of the centrifugal fan.

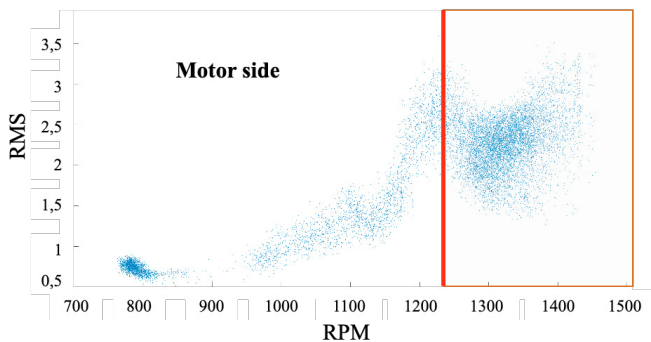


Figure 11. Scatter plot of RMS vs RPM on the motor side.

This evidence opens an intense discussion in the maintenance department, to understand why this trend shows up and what is the effect on the health state of the centrifugal fan. However,

this is just an initial integration step, solely building on a few characteristics measurable from vibration and SCADA data (respectively, RMS and RPM). Also, the research team aims to extract additional information from the available data, broadening the integration of vibration and SCADA-sourced data. Currently, the selection of the best AI (Artificial Intelligence) method is undergoing, and Neural Networks (NNs) are under consideration given the supervised problem. The selected method will take as input the available data to predict the value of the ΔP_{pred} (predicted ΔP) and then, by measuring the prediction error, notify a possible deviation from normal behaviour of the industrial fan in relation to bag filters states, based on the current working regime of the fan itself. The solution should be verified and assessed so to comply with technical constraints and barriers related to algorithm deployment, computational power, response time and others. Finally, the developed algorithms should be able to scale between different indenture levels of the asset, providing information on the health state and possible diagnostics and prognostics of faults at both component and asset levels.

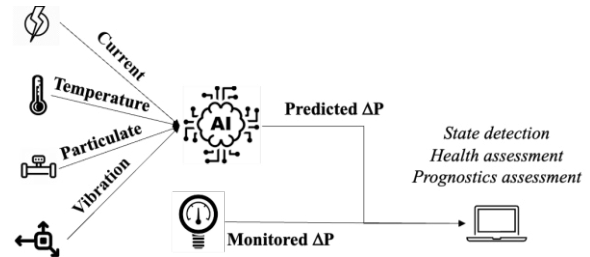


Figure 12. Future analysis with AI-based system.

7. RESULTS AND CONCLUSIONS

This work describes the experience of an ongoing project in a foundry. The project aims at developing an advanced CBM system for high-critical industrial fans that are used to remove hot and cold flue gases from the shopfloor so to guarantee a safe working environment. The criticality of the assets thus relates to their functions in guaranteeing a safe workplace and efficient operations.

The CBM system has been built considering the availability of data from SCADA as well as additional sensors, namely accelerometers, installed on the centrifugal fan. The vibration signals are elaborated according to the guidelines provided by the ISO 10816-3 (up to state detection) and ISO 13373-3/5 (for health assessment). The results show that it is possible to use the RMS as relevant feature for both state detection and health assessment of bearings. The SCADA-sourced data are used, but the retrievable information content is related to the identification of the working states of the industrial fan (if on, off, transient off, transient on) rather than on novelty detection. At the moment, the CBM system is deployed as proof-of-concept and before the final deployment additional data analytics will be introduced.

This project experience has shown interesting evidence for companies willing to pursue the benefits of CBM:

1. Vibration remains a useful signal to understand the health state of rotating machines. This is not

unexpected since from the basics of the P-F curve it is already known that vibration is one of the main early symptom of a potential failure (Moubray, 1997). Available international standards, as the ISO 10816 and 13373 support the development of CBM systems based on vibration analysis.

2. Complex assets usually have automatic regulation system, which guarantees to keep the ΔP fixed, in case of industrial fans. However, the inner control may mask the behaviour and degradation of the asset. Correctly considering this phenomenon is vital to optimise algorithm performance, while providing useful information to the maintenance engineer.
3. Despite the digitalisation, current assets are monitored so to gather process-related data. However, these data are useful to describe the working states of the asset rather than its health state. This should not be seen as a limit, but rather as an opportunity: current CBM approaches are focused on the introduction of working states as relevant knowledge so to normalise state detection results and take suitable maintenance actions.

As an additional takeaway, the maintenance manager recognises the relevance to have a reference model, referring to the PHM as in the ISO 13374, so to promote the understanding of the entire program to maintenance engineers and data scientists as well as to plant and company managers to guarantee their commitment. Concluding, the maintenance manager has already envisioned, and he is already working on, a further enhancement in the overall management of the industrial fans. Indeed, the better knowledge of the assets allows to re-evaluate and improve the service contract with the outsourcing company in charge of fans maintenance. Hence, maintenance interventions could be better defined according to current industrial fans health states.

The envisioned approach, based on a further integration by means of proper AI methods, will be expected as a future step to increase the capabilities of advanced CBM solutions for the industrial fans under study. Especially, the integration of information about the scheduling of the die casting operations is expected to improve CBM performance given that the load on the industrial fan highly depends on the flow rate of flue gases to remove. As such, AI methods such as NNs could rely on more input features, which are significant to predict the ΔP according to maintenance operators' knowledge.

ACKNOWLEDGEMENT

This work is the result of a multi-year project (2020-2021) framed within the MEGMI executive master (Master Executive in Industrial Asset Management and Maintenance, [link](#)) held by MIP - Politecnico di Milano Graduate School of Business and by SdM – Scuola di Alta Formazione, University of Bergamo. In 2021, the MEGMI master ranks in the first place in the EdUniversal BestMasters Ranking in “Industrial and Operations Management” in Western Europe.

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