Development of a flexible data management system, to implement predictive maintenance in the Industry 4.0 context

Vincent Ciancio [a,b], Lazhar Homri [a], Jean-Yves Dantan [a] and Ali Siadat [a]

[a]Arts et Metiers Institute of Technology, Université de Lorraine, LCFC, HESAM Université, Metz, France; [b]Plastic Omnium, Clean Energy Systems, α-Alphatech, Venette, France

ABSTRACT

In recent years, the way that maintenance is carried out has evolved due to the incorporation of digital tools and Industry 4.0 concepts. By connecting to and communicating with their production system, companies can now gather information about the current and future health of the equipment, enabling more efficient control through a process called predictive maintenance (PdM). The goal of PdM is to reduce unplanned downtimes and proactively address maintenance needs before failures occur. However, it can be challenging for industrial practitioners to implement an intelligent maintenance system that effectively manages data. This paper presents a methodology for developing and implementing a PdM system in the automotive industry, using open standards and scalable data management capabilities. The platform is validated through the presentation of two industry use cases.

1. Introduction

Predictive maintenance (PdM) is a proactive approach to industrial maintenance that aims to improve quality and productivity by predicting and preventing equipment failures before they occur (Chen et al. 2011). By collecting and analysing data about the behaviour and performance of industrial equipment, PdM systems can generate alerts about potential failures and allow maintenance to be planned more efficiently, reducing the impact on production schedules.

Implementing a PdM system can be complex due to the continuously evolving nature of the methodologies and tools used (Sheppard and DeBruycker 2018), as well as the specificities of different industries. To address this, it is important to develop a standard methodology for defining a PdM system that is flexible enough to be adapted to the specific needs of the industrial context. This may involve the use of multiple communication protocols for data collection, and a scalable data storage solution to accommodate the volume and variety of data generated by the PdM system.

In addition to improving maintenance efficiency, PdM systems can also help to reduce operational costs, improve product quality (Takata et al. 2004) and increase customer satisfaction by minimising the number of equipment failures and downtime. It is therefore an important area of focus for researchers, as well as for companies looking to optimise their manufacturing systems and remain competitive in today's global market.

Consequently, this research work proposes a full methodology to develop an Intelligent Maintenance System (IMS) that will help deploying operationally PdM. In addition to this methodology, the practical implementation of the system is detailed, as well as the tools included in the platform. The system is confronted to real industrial cases, in the context of automotive industry. One of the major contributions of this work is the proposition of an IMS that is non-domain centric, and flexible enough to be improved and tailored to the potential specificities of the industrial context in which it is used.

The remaining of this paper is organised as follows. Section 2 proposes an overview of approaches related to the implementation of intelligent maintenance systems. In Section 3, the motivations behind this research work are detailed, based on the review of the literature and the observations made in our industrial context. Section 4 presents the methodology employed to deal with PdM practically, which is the base of the developed solution presented more in detail in Section 5. The architecture as well as the different blocks that compose the system are described. In Section 6, we propose to validate the IMS

CONTACT Vincent Ciancio vincent.ciancio@ensam.eu Arts et Metiers Institute of Technology, Université de Lorraine,LCFC,HESAM Université, F-57070 Metz, France; Plastic Omnium, Clean Energy Systems, α-Alphatech, 60280 Venette, France

on two industrial cases. Finally, a conclusion and some perspectives are proposed in Section 7.

2. Literature review

The maintenance field has evolved over the recent years, moving from corrective actions (when failures already happened) to a predictive approach. With the advances in data processing, information coming from the production systems now allow the assessment of their current and future health state. Because machines and processes are becoming more and more complex to deliver new features to products, maintenance is impacted and requires more advanced skills and knowledge to deal with potential issues (Gouriveau, Medjaher, and Zerhouni 2016). It is therefore a necessity today, for any company seeking performance, to strive toward PdM.

Predictive maintenance is currently the most active topic in the maintenance field, as it is highly linked with Industry 4.0 and the availability of data within companies. This increase of interest for this topic is easily understandable in the context of Cyber-Physical Systems (CPS) and Industry 4.0 (Lughofer and Sayed-Mouchaweh 2019). The opportunities for predictions based on data analysis are numerous thanks to Internet of Things (IoT) and CPS, and therefore the maintenance activity is a great candidate to extract value from those analyses and improve its performance (Yan et al. 2017).

To understand further why maintenance has been in the spotlight recently, we need to go back in time and see that historically, the maintenance activities were tagged as 'necessary evil' or that they were a 'cost-centre', meaning that they only generated costs and no profits (Al-Najjar 2007; Chesworth 2018). Twenty years ago, Mobley (2002) addressed this issue by explaining that these statements were already old-fashioned back then, mostly due to the development of Information and Communications Technology (ICT). Its application in the industrial context for maintenance improvement purposes helps removing unnecessary costs and reducing occurrences of catastrophic breakdowns.

However, as mentioned by Fusko et al. (2018), many industrial companies are still not ready for that digital transformation of maintenance, as it requires advanced CPSs and ICTs, with skills that are not yet well developed within the organisations. This digital transformation not only brings new tools but also changes completely the way maintenance topics are being worked on, compared to how it was handled in the past. As mentioned by Levitt (2003) two decades ago, these changes deeply impact organisations and bring new roles in companies to implement PdM systems.

To emphasise on this last statement, we can see in Murty and Naikan (1996) that the researchers discuss the optimal time interval to make measurements of physical data on the equipment, to assess the health state degradation and propose an optimal Condition-Based Maintenance (CBM) system. This research work illustrates the rapid changes in the technology available as of today, to monitor industrial equipment's behaviour.

Cui, Wang, and Li. (2021) assess the impact of maintenance actions, failures and quality issues of the performance of the production system, then a PdM decision model helps determining the optimal scenario, to reduce maintenance actions and costs of production. In this study, a quantitative data-driven method is proposed, on discrete events, and not on real-time assessment of the equipment's health.

Data can be of different type and nature, and can be used for various activities in the PdM framework. For instance, it can be used to schedule maintenance actions when a degradation is observed. Xia et al. (2013) propose a framework for CBM to collect and analyse data from the production system to propose an optimal maintenance scheduling. This is enabled by determining a critical level of the health's state of the equipment, and the analysis of available time window to carry out the corrective maintenance actions. In this research work, however, the data management system is not detailed. He et al. (2017) describe a novel approach to PdM that integrates product quality control and mission reliability constraints. The approach aims to optimise PdM scheduling by minimising the total costs, including the costs of corrective maintenance, planned maintenance and quality losses over the planning horizon. To do this, the study defines mission reliability as a comprehensive measure of the level of equipment health needed to meet production task demands and uses it to characterise the production state. Planned maintenance is performed when mission reliability reaches its threshold. Koomsap, Shaikh, and Prabhu (2005) propose an architecture for integrating condition-based maintenance scheduling with the machine-level process control. It involves the development of an intelligent controller for a distributed system. This controller is responsible for monitoring the condition of the machine and recommending optimised operating parameters. The goal of this approach is to prolong the machine's lifetime and maintain productivity by adjusting operating parameters and providing a ready-to-run condition-based maintenance schedule.

Data can also be used to train machine learning models for PdM purposes and create new maintenance rules. Raheja et al. (2006) detail a conceptual framework for CBM, to define the use of data fusion and data-mining techniques on the different steps of the CBM system. Such steps include the detection of faults on the monitored equipment, create association rules to detect patterns in the collected data or planning corrective maintenance actions from the results of the analyses. The authors mention that future works based on this framework should include the development of an implementation strategy, to validate the model in the industrial context. Rai et al. (2021) discuss machine learning for Industry 4.0 applications and mention multiple works for PdM as in Wang et al. (2021) and Yang and Rai (2019). Ayvaz and Alpay (2021) and Bourezza and Mousrij (2020) also propose the use of machine learning approaches, to create meaningful information from the collected data, to feed the PdM system. Lee and Pan (2017) propose several integrated Markov chain–Bayesian network (BN) models for forecasting system reliability to implement PdM. The proposed models are designed to be applicable to any multi-level hierarchical system where the reliability of components, subsystems and the overall system is stochastic. Among the three models, the discrete-time semi-Markov chain (DTSMC) model performs best in terms of fitting real data. This suggests that the proposed integrated Markov chain–BN models may be useful for forecasting system reliability and implementing PdM in practice.

As data is at the centre of the PdM system, defining a data management system to handle it for the various activities inside the PdM framework greatly matters. Cerquitelli et al. (2021) discuss this data management system as 'services' to ease the implementation of predictive maintenance. Numerous software are used to define the system and the different steps linked with the activities of PdM. Traini, Bruno, and Lombardi (2021) describe a framework for PdM that can be applied on a generic industrial machine. It discusses the importance of data selection to train machine learning models, to predict the future health state of an equipment. Such considerations can help reducing the amount of data needed, as well as the calculations done to obtain more features. Schmidt, Wang, and Galar (2017) and Garcia et al. (2019) propose solutions to address the requirements of a Pdm system in terms of data management and activities to be carried out to deploy such complex system.

3. Motivations

Observations from the literature on the implementation of the PdM framework highlighted the necessity to develop a specific application to deal with it, in addition to the implementation of an efficient data management system. Some important features specific to PdM activities should be included within the solution. Such features are summarised below.

- Collect data from a variety of sources, using different communication protocols
- Process the data in various ways, with the flexibility to add additional types of processing as needed
- Monitor the data using different approaches, such as threshold monitoring, with the ability to add additional approaches
- Assess the state of the data and generate indicators to track its evolution
- Alert the maintenance team and create action plans based on prognostics
- Provide efficient visualisations of all the different steps involved in data manipulation.

Figure 1 helps understanding where this Intelligent Maintenance System (IMS) intervenes on the different

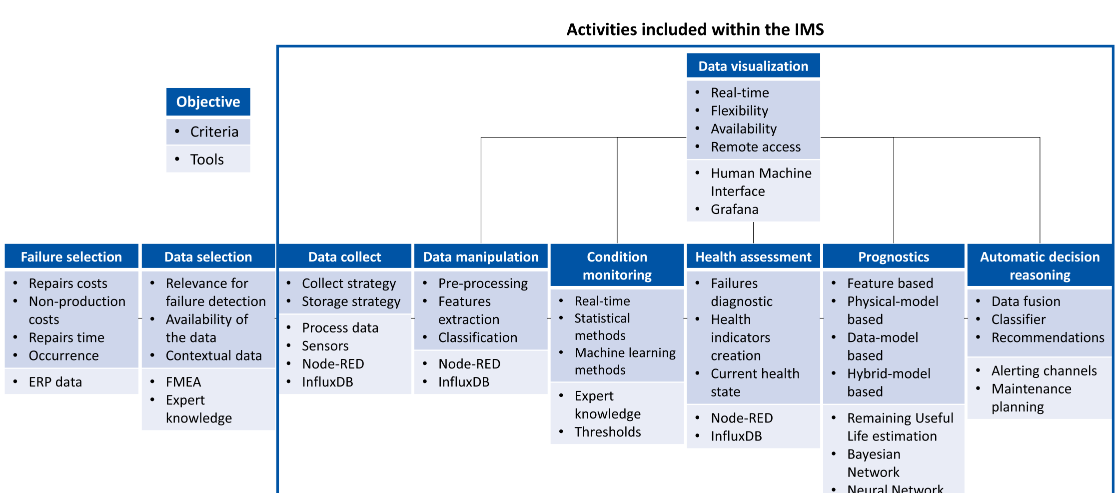

Figure 1. Perimeter for the IMS activities.

steps of the framework proposed in Ciancio et al. (2020).

Failure and data selection steps are not included in the application, as they require maintenance data from the ERP system, as well as knowledge from experts on failure modes. Consequently, these two topics are conducted manually in the current architecture of the system. The rest of the activities are incorporated inside the system, to provide a standard way of developing and deploying PdM solutions. The methodology used to develop the IMS is detailed in the following section.

4. Methodology to develop the IMS

The model that was developed around the first framework can be found in Figure 2. It presents an overview of the different steps taken to implement PdM. The application that integrates a large part of the methodology was named Machine Health Management (MHM) and proposes a set of tools that tackle the different challenges of PdM. The various parts of the methodology will be described below.

The first step in the process of implementing a PdM solution is to thoroughly understand the machine or production system being studied. This involves identifying the various components and functions of the machine and understanding how they can fail. The failures that are most relevant to study are those that have a significant impact on the machine's availability and productivity, as well as those that are costly or have a high occurrence rate.

It is important to prioritise the failures to study based on their impact and occurrence rate. Failures with low impact and low occurrence are not likely to benefit from a PdM solution, while failures with high impact and high occurrence should be addressed early on, as they may be caused by design issues.

To study the relevance of the failure modes to be studied, we propose three main solutions that are studied in parallel. These steps are the most important ones because they will define the final solution that will be implemented.

(1) The Computerised Maintenance Management System (CMMS) is a tool used to organise, track and maintain a record of all maintenance activities within a company. It can be linked to an enterprise resource planning (ERP) system to understand the costs associated with spare parts. By analysing past data on the production system, the CMMS can help to prioritise the different failures observed based on their costs and occurrences. If a new production system has no historical data, the CMMS can be used to update the list of failure modes identified through other methods at a later time.

(2) Failure Mode and Effects Analysis (FMEA) is a widely used tool in industry for identifying potential failures and understanding their causes and effects on equipment. It can be adapted for different purposes, such as analysing processes (PFMEA) or assigning a criticality score to failure modes (FMECA). In the context of this methodology, FMEA provides a list of failure modes that can be studied for PdM and helps to choose the data to be collected by the PdM system. It can also be used to identify potential failures in the early stages of a production system's design.
Second, the a-priori knowledge of causes and effects can help choosing a first set of data to be collected by

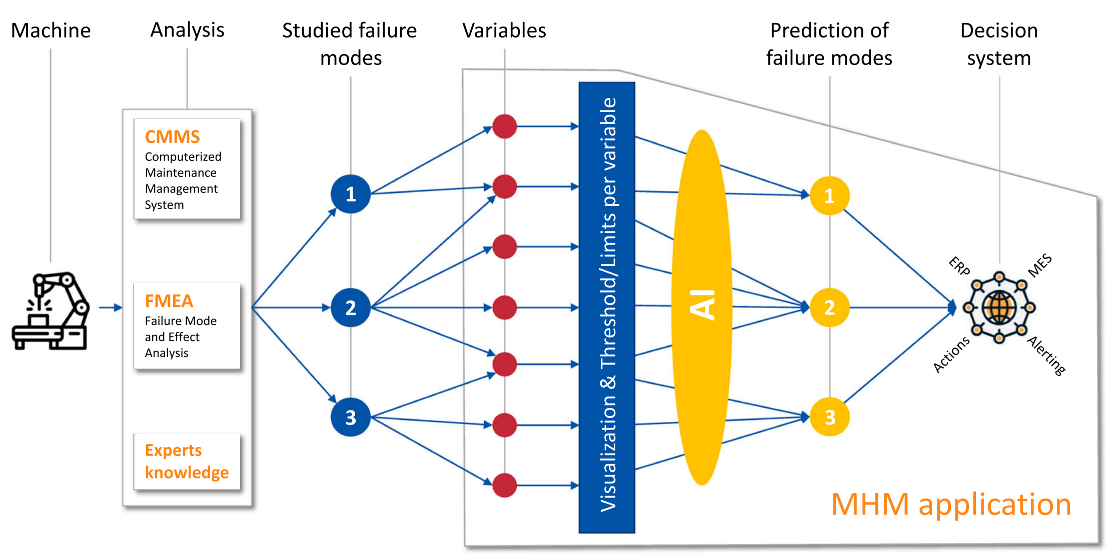

Figure 2. Machine Health Management application model.

the PdM system and even help implementing extra sensors on the production system.

(3) Experts' knowledge is also important in selecting the correct failure modes and data to be collected. This knowledge can come from a variety of sources within the company, such as process engineers, automation engineers, machinery design departments, maintenance technicians and operators. It is important to involve a wide range of experts to ensure a comprehensive understanding of the potential failures that may occur on the equipment.

As explained by Zăvoianu et al. (2021), expert's knowledge can be of different nature. In most cases, it is incorporated in the system in the data selection phase, where the relevance of the data to study a failure mode can be assessed prior to collecting it. It can also intervene in the development phase of a monitoring rule, to analyse the behaviour observed in the data, and implement first algorithms based on experience and known causes for the failure. There is a practical reason behind the selection of only several impacting failure modes to be studied, compared to, for instance, a full assessment of the production system. The latter study can be successful but involving several failure modes and a large amount of data in the PdM system can prove to be very challenging to tackle. The risk is to propose a final solution that will be too fuzzy for the end user regarding prediction of health state or not precise enough to take the correct actions. That is why, even if the solution is identified as data-driven, meaning that the model uses data analysis to propose solutions, there is still a necessary part of physics understanding involved, to correctly apprehend the failure mechanisms. When implementing a PdM system, it can be more meaningful to have a smaller dataset, but with data that has high correlation with the failure mechanism that is being studied. Knowing key characteristics related to the process can also help finding the relevant parameters to be monitored.

The previous steps give a first interpretation of the dataset that will be needed to study the selected failure modes. The next step is to identify if this data is available in the production system, i.e. the application will be able to connect to the source of the data to collect it. Many ways exist to connect and collect data through different protocols, and some will be presented in Section 5. To be successful in this step, knowledge about the automation system used, as well as Information Systems and Services (IS&S) is required. If extra sensors need to be implemented in the system, it is necessary to verify that the addition of such means of measurement will not create extra failure modes or weaknesses in the system. It means that the sensors should be as less intrusive as possible regarding the way they are implementation on the studied equipment.

There is also a requirement during this step to study and estimate the amount of data that will be collected and stored. The choice of data retention (meaning how long the data will be stored before being backed up or deleted) is of importance, as the system will grow more and more with new studies being implemented. As shown in Figure 2, this data (or variables as named in the figure) is the input of the system that composes the PdM application. Most of the data collected from the production system is time series data, but other types of data can be integrated, such as images (from 2D cameras or thermal cameras for instance). As per the figure, one variable can be used to analyse multiple failure modes, although it is only collected once.

As mentioned before, the first knowledge coming from data is most of the time with an efficient way of visualising it. The main reason is that until implementing such system on the industrial equipment, it can often be seen as a 'black box', meaning that the users cannot fully understand what is physically happening during the process. Time series data show the evolution of the system over time and close to a real-time visualisation (data can be collected every few milliseconds). It is a first strong step for the users to understand the machines and processes better and can also generate ideas about how the data should be monitored. An explanation is proposed in Section 5 regarding the users' interactions with the application.

Thresholds or limits are often the first type of monitoring that will be done on new studies of failure modes. These values can be known a priori from how the process works, or the acceptable limits of the mechanical parts that compose the production system. This first monitoring will also help implementing a first set of alerts for the users, in case of deviation.

After these first interactions with the collected data, the next step is linked with Artificial Intelligence (AI), in its broad definition. The main goal at this stage of the methodology is to be able to create correlations between selected data to predict appearance of the failure mode. It can be reached using various methods involving several manipulations and transformations on the data, which are available in the application. The data management system must integrate modules to perform these actions, such as implementation of machine learning models. Most of these analyses are multivariate because interactions and correlations between state of several data must be studied and taken into consideration. The idea here is to create a specific monitoring for the failure mode, to be able to alert afterwards and point as precisely as possible where the issue is located on the impacted production system. This precision allows the maintenance teams to be more prepared and plan specific actions related to the result proposed by the system.

Finally, the decision system is composed of numerous tools to share the correct information at the correct time and to the correct information system or user. There is a necessity to connect this PdM application to the most important information systems of the company, such as the ERP described at step 1, or the MES to plan maintenance actions without disturbing the production. The system should also have the possibility to send action plans or work orders through the CMMS. It is also important that alerts can be sent from different channels to reach the users, the most commons being emails, SMS, internal communications applications such as Microsoft Teams. Standard alerting dashboards exist for visualising data in different ways, and users also have the possibility to create new ones, so that the production and maintenance teams can easily check the evolution of the equipment's state.

5. Architecture of the application

In this section, the actual architecture is described, as well as the different possible ways to use this application. To understand how the application works, a simplified overview is proposed in Figure 3.

The application can be seen as being on top of the Edge Computing architecture. It interacts directly with it through a web interface, which will generate code without having to type it. The benefit is that it helps users visualise and understand how the machines behave, by using standardised applications. The different modules of the application are described below.

MHM is a central tool developed during this research work in Java, which stores each models used to collect, store and analyse the data at a global level. It is accessible through a web page for any user having the necessary credentials. It implements all the previous models locally in the plant, where the user wants to create a monitoring. Once this code is pasted, it runs on the local server or computer of the plant. One of the main advantages is that MHM opens this kind of monitoring to workers that do not necessarily have a coding background.

As a result, they can use the visual interface to configure what machine they want to address, what data they want to collect, how long they want to store it, and what data manipulations and monitoring they want to add. Once this configuration is done and validated, the application will automatically generate all the necessary code with the correct configuration inside the local plant device.

Because the local device is connected to the same network as the machines, it can connect to them using various communication protocols, for instance OPC UA Leitner and Mahnke (2006), Modbus (Swales 1999), MQTT (Hunkeler, Truong, and Stanford-Clark 2008) and directly to the Programmable Logic Controller (PLC) of the machine through its proprietary protocol: Siemens S7 protocol for example (Beresford 2011). Once this connection is done, data is stored locally, in a standard way, with possibility to add some extra information on the data, such as tags. This allows filtering the data for visualisations and analyses.

Some pre-configured dashboards were developed during this work, so that the users can visualise directly the

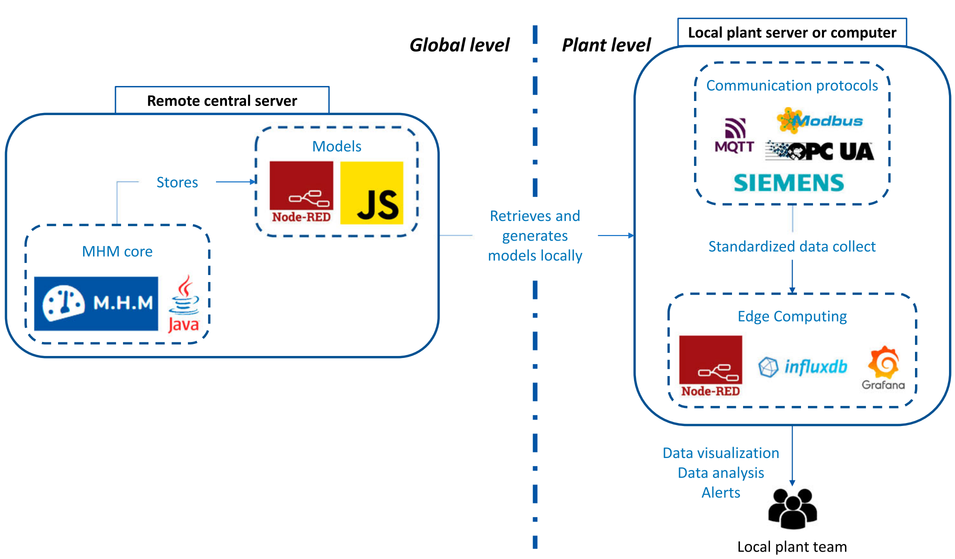

Figure 3. Overview of the structure of MHM.

newly collected data. Dedicated dashboards can also be created in Grafana, which can then be shared amongst plants. There is also the possibility to put in place some alerting regarding the monitoring rules, through the communication channels described before.

The different rules are part of the 'AI' block shown in Figure 2. They are based in the current version on static thresholds, duration of known anomaly states, catching and counting events in the incoming data or dynamic thresholds using SPC (Statistical Process Control (Oakland 2007)). SPC allows calculating thresholds dynamically, by selecting a time window reference for the data. It makes it possible to create efficient control charts, to understand if the data is stable or deviating. Each rule can trigger a specific alarm to alert the maintenance teams, and the most advanced rules can also generate work orders to plan corrective actions directly with the ERP-CMMS system. There is also a possibility to combine several rules and generate targeted alerts if the root cause of the failure detected is known.

Finally, the importance of this step is that the user is still able to reach the 'back-end' of the application (directly in Node-RED), to make some manual modifications, or even adding specific local monitoring. Plants tend to have more and more local skilled people on these topics, able to help with the coding process. In this case, the code can be written in JavaScript in Node-RED and there is also a possibility to create analyses in R or Python.

This final step is important to underline, because as mentioned before, it is quite challenging to address all the existing machines within a company. Machines may differ, not in terms of process but of components used to build the machine. Therefore, the behaviour of one machine to another may drastically change and can also be impacted by the environment in which they operate. That is why this notion of flexible tool matters, because it is not only a top-down application but also bottom-up.

The top-down aspect is linked to the developments made by the central team working on Industry 4.0 topics, which proposes specific monitoring on top failure modes directly to the end users, i.e. the plants. Using the application, they can replicate a model developed by experts and operate it directly with the correct configuration.

The bottom-up aspect is linked to the local developments made on specific issues, which can be also of interest for other plants. One of the main interests is that these developments can be done easily and quickly, on faulty equipment, which can increase the efficiency of the model created. These local developments can then be reinjected locally to other plants that may find themselves in the same situation as the original plant. Storing the models centrally, like in MHM, allows this way of working: the application can be seen as an 'application centre' similarly to what can be found in smartphones. A summary of these activities is shown in Figure 4.

6. Case study

After understanding the methodology behind MHM and its architecture, we will analyse its application in the industrial context on two different topics.

6.1. Helium leak testers

6.1.1. Principle of the process

The first topic deals with helium testing machines, also called Helium Leak Testers (HLTs). These machines intervene at the end of the production process. Their goal is to ensure that each produced fuel system is within acceptable range regarding leakage. Indeed, as mentioned

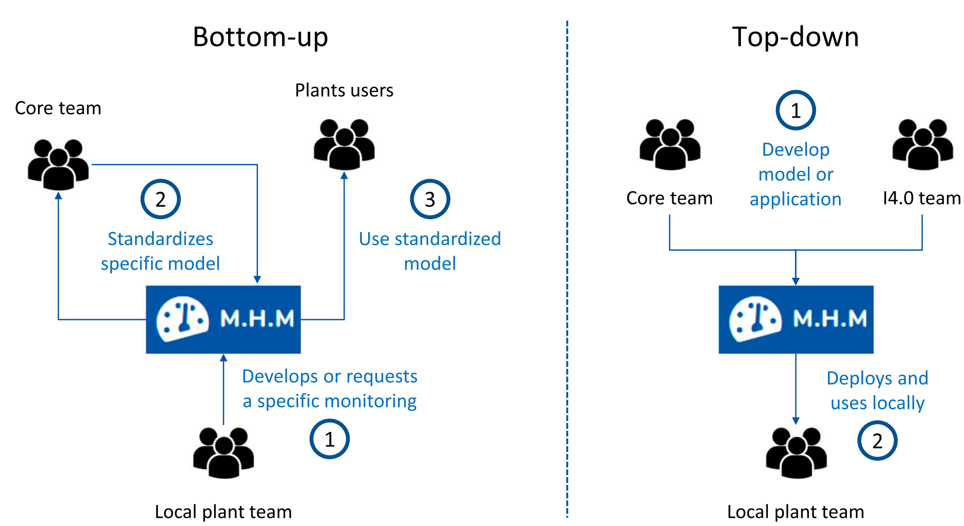

Figure 4. Top-down and bottom-up aspects of MHM.

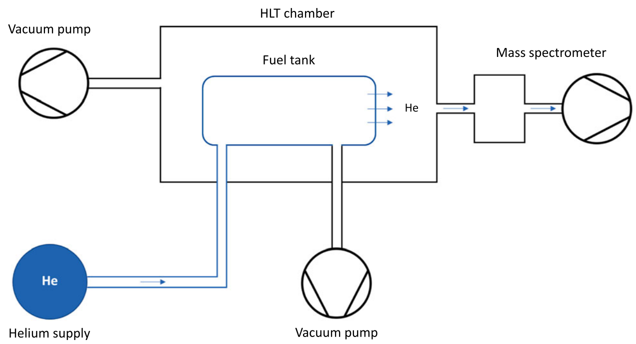

Figure 5. Helium leak test principle.

previously some cutting and welding operations are done on the tank, which can create internal leaks if the operation is not performed under good conditions.

To verify this, tanks are tested inside the HLTs. A basic principle is proposed in Figure 5.

The machine is composed of a chamber where the tank is installed. It is sealed, and vacuum pumps evacuate the air in both the chamber and the tank. Once it is complete, a fixed quantity of helium is injected inside the tank, and a mass spectrometer coupled with a pump observes the number of particles located inside the chamber, i.e. the estimation of the leak rate of the tested tank. The acceptable limit is given per product, and if it is crossed, the tank can be re-tested or defined as a scrap. Helium is used during this test as it is the smallest known atom, therefore giving a good idea of possible leakage issues on the product.

6.1.2. Topic definition

Issues on the HLTs are part of the list established regarding the failure modes to study with PdM, the main reason being the lack of internal knowledge regarding their failure modes. Indeed, these machines are historically less common to perform the leak tests, Water Leak Testers being more used globally. However, HLTs are much more complex and more efficient in the detection of leaks, therefore they are becoming standard machines to be used in production lines nowadays.

HLTs are a good example of what usually happens in the industrial context: these machines are quite complex and have many unexploited internal data that could help understanding better their behaviour. Consequently, HLT machines were selected as a first topic to be worked on using the MHM application. This use case started as a Top-Down project, as the main goal was to propose a global solution to be deployed and used within each plant.

As a first step to define the study, four activities have been performed in parallel, to understand better the issues related to this family of machines.

Table 1. Known failures on HLT machines.

Issue	Effect	Verification in place
Faulty pump	Increase cycle times Impossibility to reach vacuum level required	Oil check Biannual pump's performance assessment
Filter clogged	Contaminate oil Increase cycle times Pump deterioration	Cyclic cleaning Replacement of part with spare
Deteriorated seal	Impossibility to run full cycle Increase cycle times	Cyclic check Replacement of part with spare
Broken valve	Impossibility to run full cycle	Replacement of part with spare

- Analyse maintenance history data to understand common failures
- Interview experts from the research centre, and plants
- Work in collaboration with the supplier of machines
- Use the test machine located in Alphatech[1] to have a better understanding of the process.

The result of these steps is proposed in Table 1. It gives an overview of the issues related and the current processes in place to correct and detect them. To understand the data inside the table, as presented before the machine has several pumps, for various purposes such as removing air from the chamber and tested part, or to remove the helium still inside the chamber after the test is done. Filters are used to restrain particles that could damage the equipment, such particles can be dust, or plastic parts that could still be on the product. Seals are important on the machine, as they ensure that the process is performed properly. Finally, many valves can be found on the machine, to redirect the different gases in the correct places.

6.1.3. Proposed solution

The machine has internal alarms, and a Human–Machine Interface (HMI) to display them to the users. However, it is possible that some alarms can be missed, due to the fact that they are not critical to the process itself, but can still indicate the start of an issue on the machine. Consequently, one of the first objectives of this topic was to collect the correct data, to start creating a history and propose valuable visualisations. With the help from experts (on the supplier and company side), a first list of data was edited, most of them being in the following list:

- Cycle times: the duration of each phase of the process is calculated within the machine
- Pressures: many pressures are measured by internal sensors, at different locations on the machine

- Leak rate: calculation the observed leak rate by the mass spectrometer
- Other data: identification of the tested part, results of the tests, number of parts tested, number of hours run for the pumps.

The data is split and tagged under two categories:

- Chamber: machines can have multiple testing chambers, so each data specific to a chamber is identified here
- General: the rest of the data, common for all chambers, is identified here.

Splitting the data as such also allowed to create an interactive dashboard where the general data and data specific to chambers are visualised independently. Selecting one or both chambers will modify the dashboard, to display the correct data. This allows the users to quickly check the interesting data.

Table 2. Leads to improve the monitoring of HLT machines.

Idea	Expected result	Related action
Observe trends on specific pressures and cycle times data	Increase or decrease of the value over time should indicate an ongoing deterioration	Implement linear regression analyses
Analysis of gases consumption	Comparison of data over time can indicate seal or filter issues	Calculate consumption periodically, or per gas bottle, and verify number of tested parts
Verify opening times of valves	An increase of duration during opening and closing phases of the valve can alarm on a failure of the valve	Calculate and monitor the evolution of the opening and closing duration
Add extra sensors on pumps	New physical data related to the pumps can help detecting oil or mechanical issues	Implement extra sensors

In addition, first thresholds and alerts were implemented, based on experience and knowledge on the process. The package standardised and deployed from MHM was composed of the data collection of the previous list, which represents around 65 variables, and the dashboard discussed previously. This first solution was the basis on which more knowledge about the machine's behaviour has been built.

6.1.4. Improvements and perspectives

After implementing the first package, the second step of the work was dedicated to improving the solution. The final goal being the proposition of meaningful messages for the maintenance teams, based on the results of the analyses done on the data, the current work is oriented towards this objective. Table 2 summarises the various actions related to the improvement of the package.

An example of the User Interface is proposed in Figure 6. Here, we can find the list of machines monitored within the plant, the status of the machine according to the monitoring rules in place and a summary of issues per machine. The user can click on the specific issues, to give more details and provide a direct link to the data visualisation.

All these developments gave the opportunity to improve the core of the application, as they can be proposed as new ways of monitoring the data collected by MHM. Figure 7 shows the two main contributions of the use of MHM for the HLT machines topic:

- As mentioned previously, the complexity of the machine, the lack of internal knowledge and the availability of unused data provided a strong basis to build efficient data collection, data visualisation and first monitoring rules to alert on potential problems
- A second step, still under improvement, gave the opportunity to list and develop specific analyses, to propose a first diagnostic related to issues on the

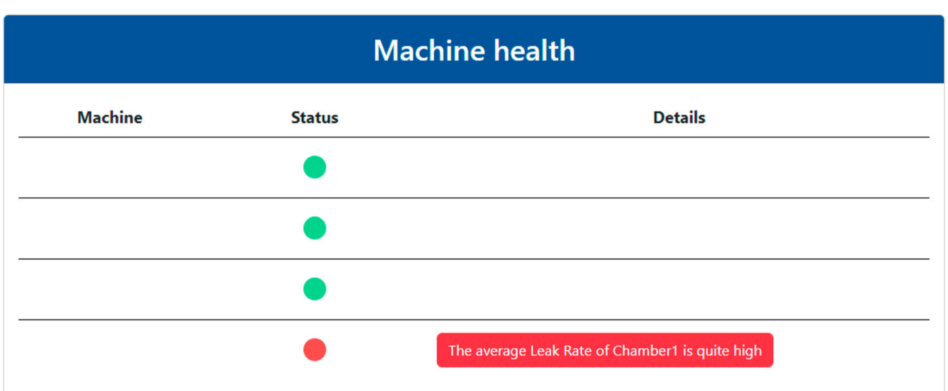

Figure 6. User Interface for the HLT machines (Node-RED).

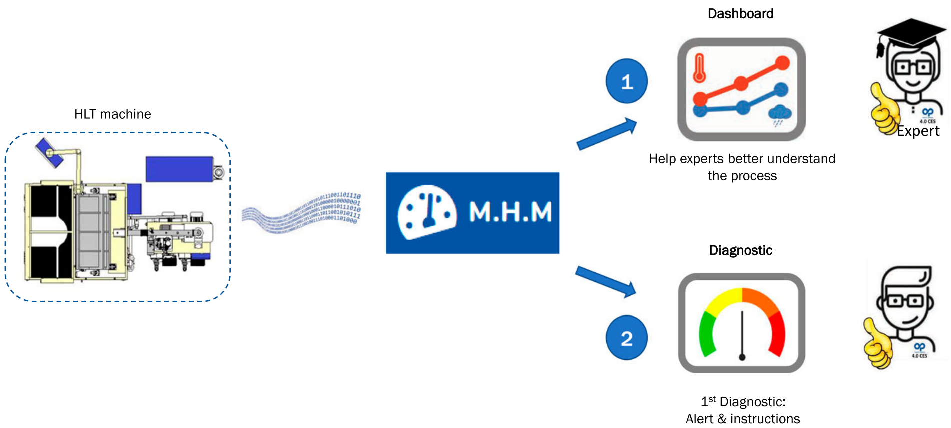

Figure 7. Current contributions on HLTs.

HLT machines. The objective is to identify clearly the observations made on data, propose maintenance actions to try and improve the health state of the machine

6.2. Blow moulding machines: band heaters

6.2.1. Principle of the process

Heating systems are found on the BMMs, on the extruders and on the head. Their goal is to keep the material melted and at the correct temperature. Similarly to the welding units application presented in Ciancio et al. (2020), the system is composed of one or multiple band heaters, and one thermocouple per 'zone'. The zones correspond to the physical location of each heating system, from the feed hopper to the start of the head. Such zones are defined in the same way for the head tooling, from the top of the head, to the start of the parison creation.

The size of each zone defines the number of band heaters that can be installed, and a regulation system powers the band heaters to reach a temperature setpoint. An internal monitoring within the machine ensures that the temperature is correctly regulated in each zone, and a detection of wrong temperature based on a plausibility test is performed, which can stop the machine if necessary. The heating systems are critical components of the machine, as any failure can lead to quality issues and severe damages on the extruders and the head tooling.

6.2.2. Topic definition

Differently from the band heater topic on the welding units that originated from maintenance data analysis, this topic was a request from three plants. The need came from several issues observed on band heaters located on the head tooling of different machines, in different plants. Therefore, contrary to the HLT study, this one can be categorised as a Bottom-Up topic, as per the definition of Figure 4. The plant located in Pfastatt, France, was selected as a first pilot for this project as several failures were reported on a specific zone of the co-extrusion machine.

Following the same steps as for the HLT machines study, we propose a summary of known failures on these components, in Table 3. The main difference with the welding units is that band heaters located on the BMMs are not moving, therefore the cabling issues on both the thermocouples and band heaters are not present in this case. The install on the extruder side is very robust, and few issues are reported. However, the setup on the head tooling can be changed depending on the production, and therefore the maintenance actions can deteriorate the components, if a wrong action is applied during this change.

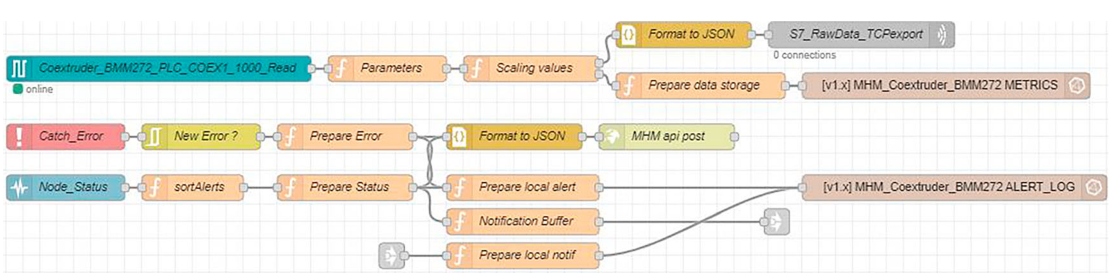

Figure 8. Node-RED flow generated by MHM to collect data from a PLC.

Table 3. Known failures on the BMMs' heating systems.

Issue	Effect	Verification in place
Band heater electrical failure	No heating possible	Monitoring with current transducers
	Brutal failure of the component	Evolution of the temperature over time
Band heater not positioned properly	Deterioration of the band heater	Monitoring with current transducers
	Regulation disturbed by zones above or below	
Band heater tightened too much on its support	Breakage of the support	Visual inspection
	Band heater loosening	
Wrong regulation parameters	Slow deterioration of the band heater	None
	Electrical failure	
Thermocouple breakdown	Loss of temperature data	Evolution of the temperature over time
	Incapability to perform temperature regulation	Stoppage of the machine

The verification currently in place on the system is linked with the evolution of the temperature, and any detection of an issue based on this analysis can stop the machine. The monitoring of the current gives alarms to the users through the HMI of the machine but does not currently stop the process in case an issue is detected. Therefore, after understanding the potential failures on the heating system, the next step presented below is dedicated to describing the available data to be collected to monitor such issues.

6.2.3. Data collect

The dataset has been defined after reviewing the system with process and automation experts, to understand the available and accessible parameters.

- The temperature coming from the thermocouple
- The temperature setpoint, which is a parameter that can be modified on the HMI of the machine
- The temperature high tolerance value, which should not be crossed during the production phase
- The temperature low tolerance value
- The PID load, named 'ED' (similar to the value of the welding units)
- The current, that is measured for one zone, meaning that the read value can be for one or several band heaters
- The current target, which corresponds to the value that should be read
- The current tolerance, below which plants' teams should be alerted
- The machine's production status.

The first eight variables are collected for each zone of the machine, and the status just once. For a typical co-extrusion machine, having 6 extruders, each of them having between 4 and 6 zones, and a head tooling having between 6 and 8 zones, the dataset is composed of around 300 variables. Using MHM, the application connects directly to the PLC of the machine, to collect each parameter every second. An example of the data collection code generated through MHM to Node-RED is shown below.

Similarly as proposed for the HLT machines, Figure 9 shows the split visualisation done in Grafana. The variables shown on top allow the selection of the necessary extruders and related zones to be displayed, and the same thing exists for the head zones. Selecting multiple extruders and/or zones will populate the dashboards with extra graphs dedicated to each of the selected items.

The machine's status allows understanding quickly in what state was the machine when visualising the data related to the heating systems. It is especially useful when checking a failure event from the history data, to get the evolution of the machine's state according to the rest of the monitored data.

6.2.4. Observed failures, proposed solutions and results

Based on the list of failures shown in Table 3, we were able to observe the first four types of failures while collecting the list of data previously mentioned. Below will

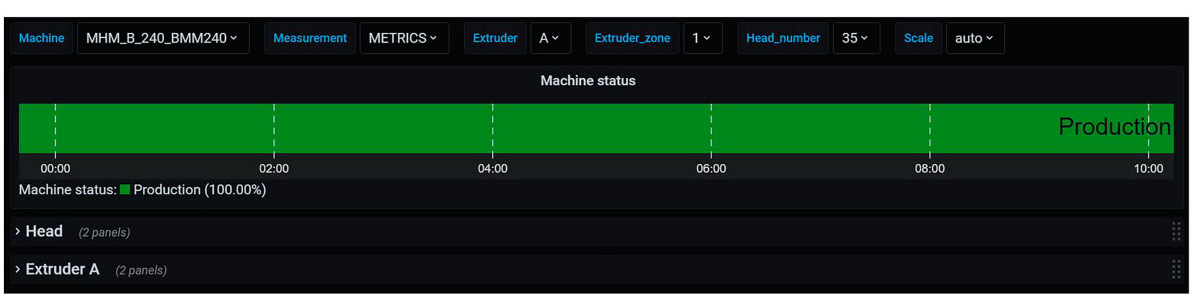

Figure 9. Split visualisation for Blow-Moulding Machines (Grafana).

Figure 10. Electrical failure of the band heater (Grafana).

be presented the different cases, and how solutions were designed within the MHM application.

The first failure is linked with a sudden loss of the component due to an electrical failure, as shown in Figure 10.

As observed on the graphs, the value of the current that powers the band heater brutally drops to 0 on the left graph ('Head_Current_35' – green curve). After this event, we can see on the right graph that the temperature is slowly decreasing ('Head_Temp_35' - green curve) and the load of the regulation is increasing to reach its maximum value of 100% ('Head_ED_35' – blue curve with vertical axis on the right side).

Due to the inertia of the system, and the zones located close to this one trying to compensate the loss of the band heater, the heating system can continue to work within temperature ranges (green coloured zone on the right graph) for several hours. However at some point the temperature crosses the bottom threshold, and the machine automatically stops, after nearly 5 hours working in a degraded mode.

The causes of the failure are numerous and difficult to observe or replicate. The data prior to the event shows no abnormal levels of temperature, regulation or current. Consequently, the first solution proposed to the plant's team was a monitoring based on thresholds and duration. As discussed previously, standard monitoring techniques are proposed within MHM, to be used on any collected data. In this case, the 'Threshold timer' monitoring uses a threshold value and a duration of the crossing of the proposed value. An additional parameter can be used, as a verification of the first rule.

Consequently, to detect and alarm the plant on the loss of the band heater, the proposed rule is detailed below.

(1) The value of the current reaches 0.
(2) The status of the machine is 'Production' (additional verification parameter).
(3) The duration of both previous rules is higher than 10 min.

Again, the main goal is to have a pragmatic approach, and setting up this monitoring to 10 min allows to verify that the signal is really lost and that the machine is still producing parts. Similarly to the thermocouple case on the finishing centres, the alerting allows the maintenance team to quickly react and organise an emergency intervention on the identified zone. As observed on the figure, the intervention took more than an hour, as it can be difficult to clearly identify where the issue is located. The current alert allows both to reduce the time of production with the broken part and to know here the replacement will be done, saving a lot of time.

The second failure observed is associated with lines 2 and 3 of the failure table. It can happen after a change of the head tooling or replacement of a defective band heater. Such event can be observed in Figure 11 and follows the previous event where the band heater was lost.

We can see from the data that after the initial replacement of the band heater, the regulation (blue curve) is following a different trend compared to the normal levels before the first failure, and after the second replacement. After investigating this event, the plant's team observed that the band heater was tightened too much on its support, creating a perturbation on the regulation loop. Eventually, the support started to break and lead to a second stoppage of the machine.

Similar events were observed, in the case where the band heater is not placed properly, and the zones above/below on the head tooling will generate a perturbation on the regulation loop. Current work is to propose a monitoring for such issue, and the first lead is to study a linear regression of the load of the regulation. Implementing such new rule will in the end also benefits other

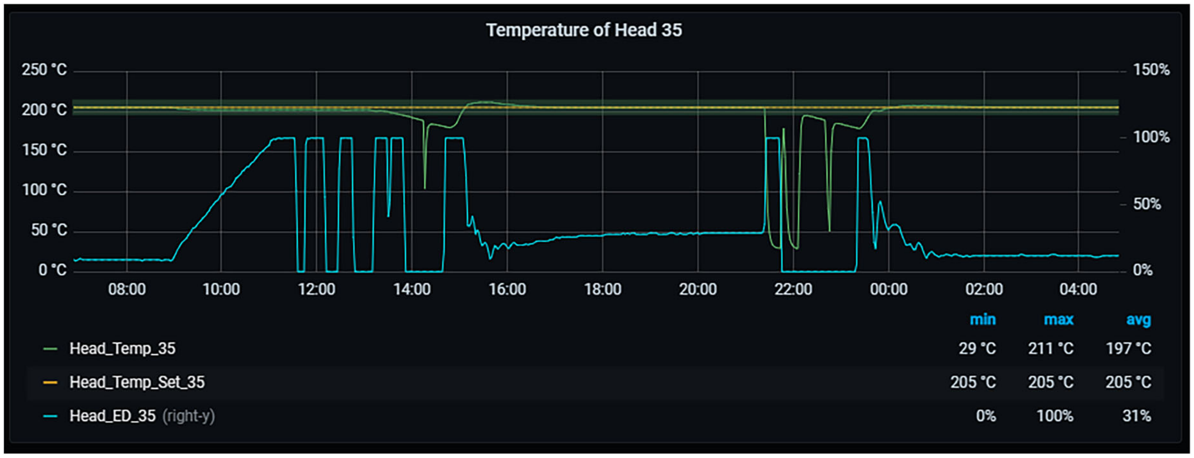

Figure 11. Wrong positioning of the band heater (Grafana).

users, as a standard monitoring 'Linear regression' will be developed and implemented within the application.

Finally, a failure linked with the fourth issue was identified using MHM. Even though it is not a common problem, it still benefited the plant and reduced failures due to such event. Investigation on the cause of the problem was quite difficult without the monitoring system in place with the application.

Figure 12 shows the effect of a regulation having wrong parameters. High instabilities are generated for several hours, and the source of the perturbation is unknown so far. However, the response of the regulation was too much compared to the effect of the initial perturbation, therefore creating an even greater issue.

These sudden changes within the regulation loop create a deterioration of the electrical system of the band heater, and eventually lead to a failure, as observed on the right graph. This failure event took place after several occurrences of the perturbation event shown on the left graph. Consequently, a specific monitoring was created, to alert the plants in case a similar issue is observed on the data, and can be linked with a wrong regulation of the system. It allows the automation engineer on site to verify and modify the parameters of the PID, if necessary.

This second example provided the opportunity to explore a concrete use case coming from plants' requests. It has been beneficial to first understand better the verification in place within the machine, to detect issues on the heating systems. From this, we could edit a list of data to be collected, which provided an interesting source of information regarding the different failures observed on the system.

The standard monitoring techniques available inside the application allowed to create ways of detecting these issues early and point out precisely which part of the system generated a problem. These information are crucial for maintenance teams because they enable them to act quickly on the correct location of the source of the failure. With the case involving wrong parameters leading to failures, we have also observed that the application is able to point out weaknesses in the process parameters and allows to better optimise it.

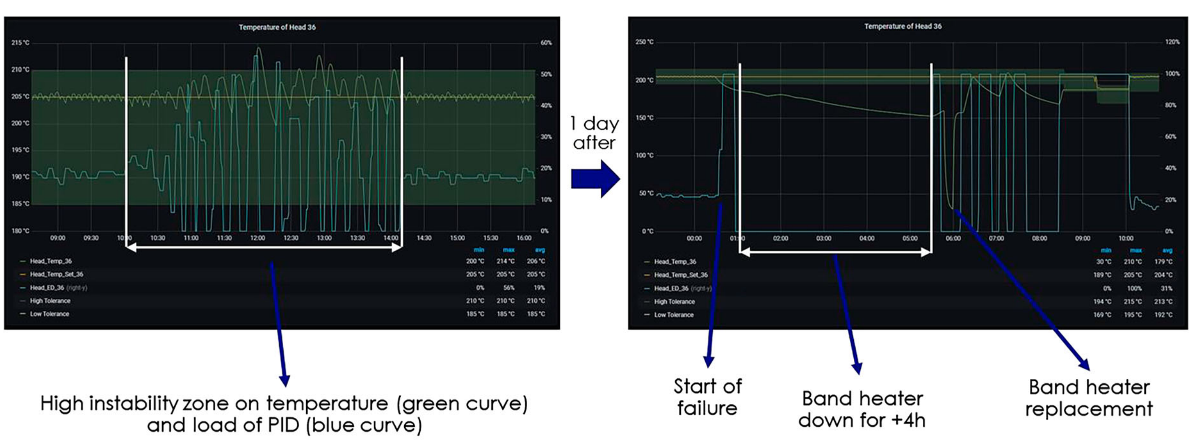

Figure 12. Wrong regulation parameters (Grafana).

We have also observed that extra monitoring are necessary, to be able to treat the various cases that can be encountered in the industrial context. This leads to improving the end solution and providing a wide range of possibilities for the users to analyse their collected data.

7. Conclusion and perspectives

In this paper, we discussed the solution developed to tackle the current challenges regarding the implementation of intelligent maintenance systems in the industrial context. The methodology that was developed behind the maintenance application is described, with all the different steps necessary to work efficiently on the failure modes of any production system. This methodology is not limited to the automotive industry but can be used in other fields and can be implemented for machines having history as well as for new equipment. The architecture that was implemented in the industrial context was presented, with a description of each module composing the system. The term flexible is employed because the application allows working in a top-down and a bottom-up way.

The main benefit of the solution is that it is built on open-source software and can be operated by users having different profiles and knowledge. It allows data exploration and creating efficient monitoring that can be used for PdM and proposes an easy way to implement solutions developed by the central team, or other users. There is a strong belief that most of the knowledge regarding machines' health state is coming from the daily users within the plants, and this tool gives them the opportunity to experiment and create broader solutions for the rest of the users.

After having confronted the methodology developed with the industrial context, several improvements were deemed necessary to propose an efficient PdM system. In this paper, we propose to move from a 'low-code' solution (i.e. the Edge Computing solution presented in Ciancio et al. 2020) to a 'no-code' solution using the Machine Health Management application. This 'no-code' aspect means that users do not need a coding background to use the solution, as everything can be configured through a web page, and the correct code is generated automatically.

This flexibility discussed throughout the paper is necessary to palliate two critical and limiting aspects of the PdM topic. First, observations and analyses on data to create a PdM solution are demanding in terms of required time and necessary resources: skilled users, availability and maturity of the information system used to develop and implement the solution. Second, most of the knowledge regarding equipment's failures is located within the plants, where users have a daily experience on the studied systems, but not necessarily the skills to develop solutions.

Consequently, proposing a system that can be used as both a platform to develop and deploy the solutions for PdM matters. It allows reducing the time of development, as experienced users on the machines can experiment with data and propose beginning of solutions that can be shared in their turn to other users. It also allows to implement these data analyses directly on faulty equipment, and local users are involved to verify the equipment's condition and make the link between events observed on the data and on the machine itself. Finally, it contributes to having more and more local skilled people to work on such topics, to balance the top-down and bottom-up aspects of the PdM solution.

Many opportunities and perspectives drew our attention while conducting this research work. We want to highlight three main topics that in our opinion will be necessary to propose an improved solution, based on this work. The first one discusses the architecture of the solution. The second topic is linked with the data selection activity that is outside of the scope of the MHM application. Finally, the last point deals with data analyses for predictive maintenance.

We would like to emphasise first on the design of the information system responsible for handling the predictive maintenance activities. We presented in this document an architecture capable of sending data to a data lake for global analyses, using machine learning algorithms to analyse the data or even generate automatic work orders for maintenance teams based on the alerts of the monitoring applications. The main point of attention on these features is that even though they were not directly used in the presented work, it is important to consider them when designing such system, as it needs to be flexible and reconfigurable. Based on the evolution of the predictive maintenance topics in the industrial context, the new findings and the results of the studies, the end system needs to be able to adapt to the requirements of the users. Consequently, these features were tested and validated in the system, to be ready for future use.

The MHM application proposes a standard way of dealing with the predictive maintenance activities linked with data handling. One of the improvements for the framework is related to data selection for failure analysis. It is a crucial step that is not always easy to perform correctly the first time. Most of the time, the choice is based on expert knowledge when it is a known issue on the equipment, however it can happen that the failure is not known or documented. As a result, there is an interest in proposing a systematic approach to select the proper data to detect and predict a given failure. To do so, a first proposition was to work on an existing approach proposed by Echeverri, Dantan, and Godot. (2021), from the LCFC laboratory. This approach aims at defining the best solution during the conception phase of a production system, using the Energetic Technical Functions (ETF). It is a representation of the energies involved in the process, to identify risks coming from them. In the case of maintenance, the interest of this approach is to make the ETF representation of the equipment or component to be monitored, to understand its function and the energies involved. By doing so, it is possible to then identify the data to be monitored, by linking the physical phenomena involved in the production of the ETF, and the risks of failures identified on the equipment. This process is still under investigation, but can help proposing a systematic approach to select the relevant data for failure analyses.

Finally, from the observations coming from the different use cases studied during this work, we highlighted that catching faulty events can sometimes be a difficult task. Having failure data is not always a possibility while working on predictive maintenance topics. In the recent years, many researchers proposed to work on data collected during a known healthy state of the equipment, to learn its representation using mathematical models. There is a high interest for predictive maintenance of some critical systems where it is not possible to generate or simulate failures. One of the possibilities is called Novelty Detection as proposed by Finch (2020). It enables to create an anomaly detection system when the incoming data is outside of the known healthy state from the model. A second possibility is linked with the transformation of timeseries data into images, to use machine learning models for image classification, as proposed by Hatami, Gavet, and Debayle (2018) and Yang, Chen, and Yang (2019). Similarly, the main idea is to label images for the healthy state of the equipment and detect faulty states as anomalies by the model.

Note

1. Alphatech: research centre of Plastic Omnium CES, located in Compiègne – France

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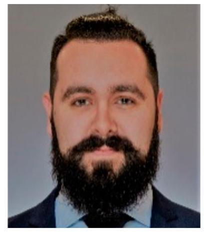
Data availability statement

The data that support the findings of this study are available from the corresponding author, VC, upon reasonable request.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributors



Vincent Ciancio is a PhD student in industrial engineering at Ecole Nationale Supérieure d'Arts et Métiers (ENSAM), France. He obtained his engineering diploma from ENSAM in 2018, a Master of Science in production engineering and management from KTH, Stockholm, and a Master of Science in knowledge integration in mechanical production, design and manufacturing from ENSAM. His research interests include Industry 4.0 topics, mainly related to predictive maintenance.

Lazhar Homri is an associate professor at Arts et Métiers Institute of Technology since 2015. He obtained his Master of applied mathematics from Aix Marseille university in 2011 and his PhD in mechanics and engineering from Bordeaux University in 2014. His research interests include Integrated Product and Process design, Tolerancing, Uncertainty management and AI.

Jean-Yves Dantan is a full professor at 'Arts et Métiers Campus Metz' since 2010. He obtained his Master of Science in Manufacturing and Industrial engineering from 'Ecole Normale Supérieure de Paris Saclay' (LURPA) in 1996, his PhD from University of Bordeaux in 2000 and his Habilitation thesis from 'Ecole Normale Supérieure de Paris Saclay' in 2009. His research interests include Integrated Product and Process Design, Tolerancing, Uncertainty management and CAPP. He has published around 150 papers and communications. He is a CIRP member since 2011. He is the coordinator of French-German Institute for 'Industry of the Future' (Institute between Karlsruhe Institute of Technology & Arts et Métiers) and of the French-German Doctoral college. He is the coordinator of several research projects: AdeQuat, RobustAM, Industrial chair, FlexSpeedFactory, etc.

Ali Siadat received his PhD in robotics and digital signal processing from Institut National Polytechnique de Lorraine in France. He started his carrier as an associate professor in computer and industrial engineering at Arts et Metiers and became a full professor in 2016 at the same engineering school. He was the head of applied mathematics and computer engineering department during 7 years and since 2019, he's the director of Design, Manufacturing and Control laboratory. He served also as a guest professor in several universities in China, Iran, Morocco and Brazil. His research interests include artificial intelligence, information system, knowledge formalisation and operations research applied to production system fields. He has published over than

60 papers in distinguished scientific journals and more than 80 papers in international conferences and he supervised more than 25 PhD theses. Ali Siadat is actively involved in Factories of the Future programme in France and his research activities are driven usually with international collaborations and very close to industries. His new research projects interest in integrated human factors to the optimisation of production systems.

ORCID

Vincent Ciancio https://orcid.org/0000-0001-5645-8369
Lazhar Homri https://orcid.org/0000-0001-6754-844X
Jean-Yves Dantan https://orcid.org/0000-0002-0491-8391
Ali Siadat https://orcid.org/0000-0002-8406-1892

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