Methodology for a practical and effective implementation of Predictive Maintenance on robots

Jessica Rossi*, Augusto Bianchini, Gianluca Di Francesco

**University of Bologna, Department of Industrial Engineering, Via Fontanelle 40, 47121 - Forlì – Italy (jessica.rossi12@unibo.it)*

Abstract: Industrial robots are used in industry by several decades, but now their integration in production lines is widely spreading to new applications, above all for processing and assembling activities. Speed and accuracy are surely two of the main required characteristics for the robots, but to be competitive in the actual industrial context, robot reliability and availability are fundamental. The maximization of asset availability is the main effort of maintenance professionals, above all for robots, for which unexpected downtime could generate very high costs due to production losses and maintenance interventions. Predictive maintenance is considered a promising solution to overcome the typical trade-off between the maximum exploitation of asset useful life (typical of corrective maintenance) and the extension of the asset uptime through preventive interventions (time-based maintenance). With the support of digitalization tools, such as artificial intelligence, the predictive maintenance (PdM) can use several information to evaluate the actual condition of a system, predict its failure conditions and estimate its remaining lifetime, minimizing downtime and improving productivity and product quality. In this way, it is possible to decrease maintenance costs reducing preventive actions on assets and spare parts in the maintenance warehouse. However, the application of PdM has been often limited by some challenges, typically linked to the incomplete perception of PdM potential in relation to the expected necessary changes. In this paper, a methodology to effectively implement predictive maintenance on robotic production lines is introduced: the elements and the activities necessary to apply different phases of a PdM strategy will be identified and compared to some already available solutions. The aim of the paper is providing initial and practical guidelines (verified in a company) to approach to this new promising maintenance policy, highlighting the requirements for PdM implementation and hence reducing the risk to fail for the lack of some unscheduled aspects.

Keywords: predictive maintenance; robotic lines; downtime reduction; data management.

1.Introduction

Among the other pillars of company competitiveness (e.g. knowledge and skills, innovation, supply chain infrastructure, business dynamism), maintenance has a key role. When managed optimally, it contributes to increase productivity, customer satisfaction and long-term profitability, ensuring efficiency of production systems, product quality, reducing operation costs and improving workers' safety (Sanches et al., 2019). Generally, maintenance costs make up a large part of the operating costs (15-60% of total production costs). However, it was assessed that the 33% is not necessary, due to mismanagement of its activities, derived from the lack of useful data to quantify repair actions (Mobley, 2002). Various maintenance policies exist and each company applies the most cost-effective one for its operations. The corrective maintenance is based on the principle of letting the asset work and keeping it in operation for as long as possible, until a failure occurs. When the system fails, the goal is to intervene and restore the initial operating conditions of the equipment as fast as possible, to restart the asset and make it work properly. Preventive maintenance is carried out on a periodic basis (Fernandes et al., 2019). The main objective is to ensure the continuous operation of the plant without any sudden failures, trying to always maintain the plant in good conditions. Therefore, preventive maintenance can lead to higher maintenance costs, since acting in a preventive manner on a failure means to replace the components before the end of their useful life (Ahmad and Kamaruddin, 2012; Bianchini et al., 2019). Predictive maintenance (PdM) is a meeting point between preventive and corrective maintenance. Since continuous dismantling and reassembling of components for periodic interventions may induce additional failure risks and higher costs, PdM aims to avoid unnecessary interventions and at the same time minimize failures. PdM is based on the assumption that a failure of any system or component derives from a continuous increase of defects or progressive degradation, which can be quantified by measuring some weak signals (e.g. vibration; temperature; current; oil viscosity and pressure) through suitable instruments (e.g. respectively accelerometers; thermocouples; ammeter; viscometer). If a mathematical correlation can be established between signal and time, it is possible to predict the remaining useful life (RUL) of the component (Sakib and Wuest, 2018). This information allows the company to schedule maintenance activities, through the generation of alarms, reducing the time of intervention and the impact on production (Bianchini et al., 2018a). To effectively implement a PdM, two requirements are necessary: (i) reliable and consistent data about assets, and (ii) an algorithm able to analyse a large amount of data and create a model. Scientific research has made much effort in recent years regarding the development of algorithms based on Artificial Intelligence (AI) (Fernandes et al., 2019; Nguyen and Medjaher, 2019; Kilic et al., 2012; Abbasi et al., 2018). This process, driven by the development of Industry 4.0, has contributed significantly to the utilization of AI tools within industrial realities (Killeen et al., 2019; Aheleroff et al., 2020; Jasiulewicz - Kaczmarek and Gola, 2019). Companies are increasingly interested in these topics and want to start approaching the utilization of these new tools. Unfortunately, they face a common problem: the lack of data. Despite the high automation level makes a great amount of information available, data are often used to manage the production, therefore specific information and alarms about the operations of the process (e.g. logical controls or strings) are visualized on that operator panel, but data that generate these information are not acquired and stored. For transferring maintenance information, paper-based records and spreadsheets remain the most used solutions, determining misunderstanding, incomplete information and delays. On the other hand, the application of machine learning technologies requires a considerable amount of high- quality data to be analyzed.

This aspect becomes fundamental when PdM is applied to robotic production lines. In recent years, the level of automation within companies has significantly increased. In particular, industrial robots are increasingly used within large companies because they make it possible to perform repetitive, heavy or dangerous operations ensuring a very high level of production capacity and flexibility (Syed et al., 2020). To increase capabilities, the integration of robots requires a series of equipment, devices or sensors required for the robots to perform programmed tasks, that makes the manufacturing environment more complex. More components means more sources of faults and failures, influencing some key performance factors of a robot (e.g. accuracy, velocity, force, torque) and seriously impacting on productivity (Qiao and Weiss, 2018). To ensure a high level of availability of these machines, robots are typically oversized for the application they have to perform, thus high reliability within industrial contexts is ensured (Valente, 2016). Today, to ensure the proper functioning of the robots, companies rely on annual maintenance contracts with the supplier, which guarantee preventive maintenance actions, telephone technical assistance and a guaranteed intervention time by a specialized technician. These contracts are onerous and involve redundant preventive actions but are stipulated due to the lack of internal technical know-how and to ensure the continuous operation of the machine. PdM is a promising solution to reduce redundant interventions and avoid unexpected downtime due to a sudden failure. However, this solution is complex to implement because robots generally have a high level of reliability. For this reason, it is difficult to obtain data about several breaks of a robot, making it difficult to create a predictive model (Paes et al., 2014; Pinto and Cerquitelli, 2019). Finally, robots are complex machines, which depend a lot on the type of tasks they perform within a production line, and there are many signals that can be acquired and analysed. Some researches, aiming at developing a PdM on industrial robots, have been conducted in the last years. Some of these focus on the determination of the correlation among one signal with the degradation of robots, typically monitored with the accuracy of robot positioning (Borgi et al., 2017; Kwon et al., 2009; Qiao and Weiss, 2018; Bittencourt et al., 2012; Sathish et al., 2016). Others aim to develop algorithms, based on machine learning, to predict robot faults (Eski et al., 2011; Pinto and Cerquitelli, 2019). However, all these studies start from a promising condition that is the availability of some data to conduct a PdM. Having proper data, in the proper format and quantity, to be processed for maintenance scheduling is fundamental, but it is not obvious for companies. It derives that it is not possible to replicate the same methodologies defined in previous researches in the industrial settings in the short terms. Some preliminary activities are necessary to prepare and guide the companies for PdM. Moreover, the trends of some data with time vary with fault types and it is difficult to describe all the faults with a single model (Borgi et al., 2017). For all these reasons, there are currently no established PdM techniques applied to robotic production lines in the industrial field.

In this paper, a methodology to effectively apply PdM to robots in industrial production lines is defined. The methodology can be applied to each company that wants to approach to PdM on robotic systems, starting from the typical management of a production plant. The proposed approach is consolidated since applied at industrial level. Some steps, although simple, are not obvious for companies, which require a guide to effectively implement a PdM strategy, to avoid the risk to install new technologies without the complete exploitation of their functionalities. As approach designed to industrial applications, the proposed methodology aims to provide the elements to demonstrate to plant and maintenance managers the benefits of PdM on specific systems (e.g. bottlenecks, high investment cost and high productivity plants), to finally boost the effective implementation of this strategy. The main difference between previous studies about the topic is related to the fact that the method is not applied to a specific robot (whit specific applications and problems), the approach is designed at plant level, considering all the robots and their relative equipment in the process. Since it is not easy, cost-effective and even useful to implement PdM on the entire plant, the method won't neglect any step that could prevent the successful outcome of PdM policy. Moreover, in doing so in the industrial application, some lacking aspects emerged, typically not described in literature since the common approach is to analyse a single robot for which the availability of data is taken for granted.

2.Methodology

For the implementation of an effective PdM on robotic lines in real industrial settings, a methodology, mainly consisting of 4 stages, is proposed. Each stage is further composed by several sub-stages, as shown in Figure 1.

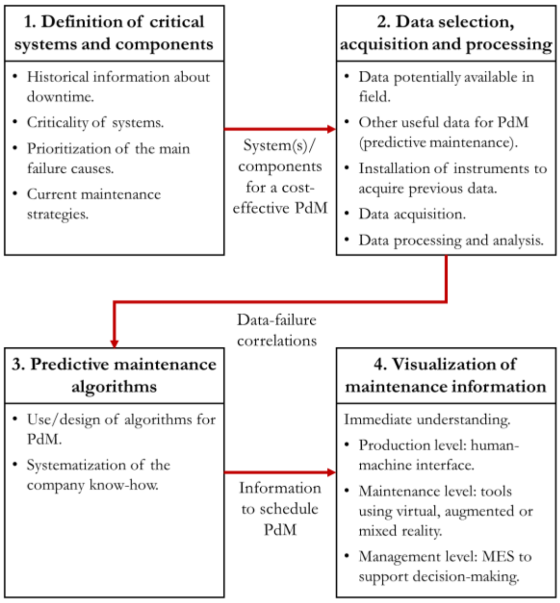

Figure 1: scheme of the proposed methodology to effectively implement PdM on robotic production lines in real industrial context

2.1 Definition of critical systems and components

The first crucial stage of the methodology to implement PdM on robotic production lines in industrial field is the identification of critical systems (and its subsystems), intended as parts of production lines containing robots and other equipment to ensure specific operations in the manufacturing process. It means to detect what assets have a considerable influence on system reliability, allowing the selection of the stations and components on which developing a cost-effective PdM policy, allocating resources and making efficient and useful actions. This stage is fundamental since the proposed methodology is defined at plant level for companies that approach to PdM. Consequently, since implementing PdM at the entire plant is not easy and even cost-effective and useful, considering the high number of systems and installed robots, plant and maintenance managers must focus their efforts (costs, time, human resources) on systems where PdM is an effectively promising solution. To determine what are the most critical systems in robotic production lines, the following activities are necessary.

(i) *Collection and analysis of the historical information about down-time*. This activity requires to collect data and reports about past failures in the robotic production line, regarding to: the involved systems and the number of times that they failed; the generated alarms; the downtime duration (preferably sorted by time to find and to solve the problem) and the typology of intervention conducted to restore the operations.

(ii) *Determining the criticality of the failures*. The quantitative information collected in the previous analysis are the basis to complete the prioritization of the systems and of their failures. There are several criteria to assess the criticality of a system (Gupta and Mishra, 2018), Table 1 shows some of them. Meetings and interviews with managers (both of production and maintenance functions) can be used to define criteria and evaluate them to assess and prioritize the criticality of the systems.

Table 1: example of criteria to assess criticalities (regarding maintenance) of systems in robotic production lines

Criteria	Description
Total cost	Sum of costs of maintenance intervention, investment for a new component and production loss.
Dependency relations	Role of the system in the production line in relation to other systems: leading role, independent or dependent.
Maintainability	Complexity of the system; necessity/availability of technical specification and expertise; ease to repair; time for intervention.
Safety	Human; resources (other assets and equipment); environment.

Identification and prioritization of the main failure causes in the system. After the determination of the most critical system(s), on which it is possible a cost-effective application of PdM, a more detailed analysis of the components in the system is necessary. It requires to identify why the system fails: it means to understand the main causes of the plant stops and the components that are influenced from them. Information about failure causes and their related downtime must be collected in a significant time period (e.g. 1 year): for example, they can be obtained by the combination of data from PLCs (Programmable Logic Controllers) and from maintenance reports. The values of the total downtime, generated in the referred period from different failure causes, can be organized into a Pareto diagram to show the most impactful causes. Given the high reliability of industrial robots, it is expected that this type of component does not fall in the causes that determine the 80% of the cumulative downtime of a system (Pareto Analysis results). However, faults and failures in the system where robots work can impact on the performance of robots, which can generate a lower product quality and a robot health degradation, until unexpected and expensive shutdowns can occur. Consequently, due to the high costs required from the installation, the operation and the failure of a robot, the implementation of an effective PdM on robots is considered in the proposed methodology.

(iv) *Study the current maintenance strategies*. The last activity of this stage is the study of the procedures used by operators to physically detect and solve the maintenance problems. Proper interviews with personnel that manage the operations and the maintenance of the system and of its components allow the collection of other information that derive from their experience and expertise, highlighting potential aspects to be improved with PdM.

2.2 Data selection, acquisition and processing

Since PdM is a data-driven maintenance strategy, the second stage of the methodology is based on the selection, the acquisition and the processing of data that can be useful to: (i) detect the main causes of system failures with sufficient advance to schedule maintenance intervention and (ii) monitor the impact of different failure events on health of robots (both in the short and the medium term). The introduction of automated technologies, as industrial robots, requires the exchange of a great amount of data to coordinate the work of different assets. Some of these data (e.g. cycle time, good and no-good parts and stop time) are typically acquired and processed to evaluate some performance indicators such as OEE (Overall Equipment Effectiveness). However, there are numerous data that effectively travel in an automated production line, but they are not registered (some data are typically visualized on operator panel). Such data could be useful for the implementation of PdM. Moreover, in recent years the development of tools and sensors to acquire data from plants has increased (Aheleroff et al., 2020). Specific instruments can be used to both monitor addition signals recognized as significant for component health assessment and/or to carry out checks and diagnoses during the operational life of the components. Some examples are: sensors for temperature, pressure, flow rate; thermography camera and inspection windows; vibration analyser; power quality analyser; conveyor chain wear monitoring system; current signature analyser; ultrasound analyser; oil sampling tools. Acquiring all data available in a robotic production line and adding instruments to measure consolidated useful data for maintenance can result in a significant additional expense, relating both the installation of technologies to measure and acquire data and the management and the storage of a great volume of information. It is always fundamental to economically quantify the benefits of a PdM policy, comparing the additional costs to implement it to the avoided production losses (Wang et al., 2017). An effective selection of data to be acquired to apply a PdM strategy is a crucial point of the methodology.

Steps to implement this stage are reported below.

(i) *Analysis of data potentially available in field.* In this phase, it is necessary to consider all the data that can be derived by the technologies already installed in the plant:

• data that are already extracted – only visualized or already stored;

• data that travel between technological assets but are not extracted to be visualized or registered;

• data that could be extracted from technologies, but, being not useful for the process, are not exploited.

This last case is typical for robots. Despite industrial robots can provide hundred typologies of data, they are not used (also by robot brand owners).

(ii) *Identification of missing data necessary to maintenance*. Having a picture of data that can be available in field, it is possible to highlight the necessity of monitoring other specific parameters that can well detect the main failure causes, identified in stage 1.

These 2 activities allow the selection of the data to be monitored since they characterize the state of critical components.

(iii) *Installation of the instruments and assets to acquire useful signal.* Except for data that are already extracted, all the other categories of data previously described, require additional technologies to be acquired. Depending on the layout of the surrounding asset and the characteristics of the working environment, the most suitable solutions to measure, acquire and store data must be evaluated, always considering the economic aspects.

(iv) *Data acquisition*. It involves design and implementation of a proper procedure to collect data, that means that the acquisition method must be consistent with the type of associated failure and with the variation of this signal with time. For example, it is not suitable to acquire a signal once a second if the health of the corresponding component progressively degrades after several years. It is important that these data are clean and accurate, as their quality greatly influences the next steps. Usually all the data are stored in a local or cloud database. This phase is very important for robots because robots are machines that depend a lot on the type of application they perform. Understanding how to read and save the operating data of a robot allows the creation of a database useful for the following analyses and that can communicate with other enterprise software. Today, database about robot is lacking in most industrial realities.

(v) *Data processing and analysis*. Once the data are stored in a database, they are ready to be analysed to find useful information (e.g. RUL). It is important to act some operations, such as applying filters to clean the signals from measurement disturbances. These activities allow considering only reliable and high-quality data, that effectively result linked to certain events.

2.3 Predictive maintenance algorithms

The stage 3 of the methodology uses acquired data to elaborate useful and significant information to schedule maintenance activities, minimizing downtime. It involves the elaboration of algorithms able to identify correlations between variations of the acquired signals and the component state degradation/failure. Learning from data related to typical operations and failures, this type of algorithms is able to set and then correct alarm levels to schedule maintenance interventions. The selection of the most suitable machine learning algorithm requires to frame the PdM model, that means to define what outputs are expected; if data are 'labelled' with the asset conditions (e.g. label: good; fault); how far in advance a failure must be identified; what are the performance targets and the risk tolerance. This information is necessary to decide what modelling strategy (e.g. regression, classification, clustering) and category (e.g. supervised; unsupervised etc.) is more appropriate to the application. Numerous applications exist and/or are under development aiming to define increasingly precise and reliable algorithms based on machine learning, able to detect faults and diagnosis and/or predict the RUL of a component. A single ML algorithm cannot fit all the desired features and a typical trade-off exists between accuracy and interpretability. After the selection of the most suitable ML algorithm, it must be validated with several tests to compare expected and actual behaviour of the model. When results are satisfying, the model must be deployed and integrated in the system (e.g. cloud, local PC, company server, embedded devices or a mixed solutions), properly selected for model computation.

Despite the difficulties related to an effective implementation of advanced algorithms, due to the great amount of data to be fed before having reliable results, the great value of this stage is the provision of a tool that systematize the know-how and the experience developed in the company. Know-how consists of the practical knowledge needed to make specific activities, in this case problem recognition and maintenance actions. This knowledge is present, in different ways, in people. Transferring this expertise in a digital tool allow the diffusion of the same knowledge without loss of information and the replication in other similar contexts.

2.4 Visualization of information for maintenance

The last stage of the methodology consists of the development of a proper visualization of maintenance information to monitor the real-time conditions and generate an immediate understanding of the necessary actions to be done. It involves three different levels, that can be supported by digital tools:

1. production level: it requires a proper human-machine interface for operators that manage the operations on the terminals. Alarms must be clear and effective to rapidly identify the generating causes;

2. maintenance level: tools that exploit virtual, augmented or mixed reality can be developed to make it easier and more rapid the intervention, providing visual indications to repair and replace faulty components;

3. management level: maintenance information can be integrated in the company MES (Manufacturing Execution System) to optimize the efficiency of single components and of the entire production lines, improve the quality of products and support the decision making about the replacement of some problematic components with more innovative ones.

3.Industrial case study

The proposed methodology is currently applied to the robotic productive lines of an Italian Company that produces household appliances. In the last years, the Company has significantly increased the number of industrial robots, installed to automate many assembling processes. The Company establishes expensive maintenance contracts with robot producers to ensure the continuous operations of the plants. However, downtime occur, in some cases linked also to robots. Since failures generate a high productivity loss, the Company showed the need to implement more effective maintenance strategies, approaching to PdM. A critical system was selected by the Company giving greater importance to the downstream stations, high-dependent from this system, that, if failures, stops the entire production generating high costs of production loss. Moreover, the selected system responds also to the criterion of complexity since it consists of several types of technologies: 7 industrial robots (4 models of anthropomorphic robots); rotary tables; conveyor belts; automated machines for specific mechanical operations. For stage 1, data about failure causes and relative downtime have been collected from daily production reports, filled manually by operator. As expected, the Pareto Analysis showed that robots were not one of the main failure causes. However, due to their importance in the process productivity, it was decided to continue the analysis also on robots.

Despite the high level of automation, the first encountered problem was the availability of data: in fact, only process data (cycle time – set and real; production and no-goods parts) were stored and alarms were visualized on operator panel. It derives that the stage 2 required great efforts to make data available for PdM. Having a great quantity of data is fundamental to create a model that describes the behaviour of the asset and estimate the RUL of a component with a certain level of accuracy. However, a deep analysis of data is still useful to understand the values of normal operation of the asset, setting alarm levels when the values of the captured signals diverge. All the possible solutions are currently under study to address the lack of data from robots. In particular, 3 models of anthropomorphic robots (installed in the selected system) are analysed. For these, 3 different ways to collect data have been identified and for each of them advantages and disadvantages are evaluated, as shown in Table 2. The goal is to use a solution that is suitable for the specific industrial application.

Table 2: solutions to acquire and collect data from robots

Solution	Advantages	Disadvantages
Robot language	• Replicable programs; • No additional software required.	• PLC reconfiguration to read parameters.
OPCUA	• Standard protocol; • Independent of PLC.	• Limited acquisition time.
External sensors	• Acquisition of additional signals, not available among robot internal variables.	• Connection with non-standard data acquisition systems.

1. *Robot language*. Solution 1 consists of programming language of robots to read robotic system parameters via PLC: each parameter must be indicated in the robot program. If the robot is already installed and operative in the asset, it is necessary to modify the operating program of the robot and the PLC must be configured to allow the reading of the robot parameters.

2. *OPCUA*. Solution 2 consists of the installation of a software on the robot controller, enabling the robot controller to industrial communication via OPCUA

protocol (Cavalieri and Chiacchio, 2013). In this way, a direct communication with the robot is enabled without having to go through the PLC. Since the minimum data acquisition sample time is 100ms, this choice is not suitable for high-dynamic applications.

3. *External sensors*. Solution 3 consists of the installation of sensors outside the robot to measure specific values, such as absorbed current, vibration, temperature. The acquisition system needs to be analysed since it depends also on the system used to read and save data. This choice entails very high costs due to the instrumentation to be installed on the robots.

Considering the industrial context of the case study, data acquisition from robot via OPCUA is considered the most suitable solution. Acquiring data via OPCUA from robots means using a versatile protocol that can also be integrated into other IT infrastructures without the use of other tools. To perform machine-to-machine communication and acquire data via OPCUA from industrial robots installed on industrial case study, 3 main activities are necessary:

• installation of an OPCUA server software on robot controller that enables the robot to communicate with the external environment. In the case study, the OPCUA server software developed by robot brand owner was selected to be installed in the robot controller. There are several releases of the OPCUA server software, which vary depending on the firmware installed on the robot controller;

• installation of an OPCUA client software that sends service and publishing requests and receive responses. An OPCUA client software was already installed on a PC to test data communication. In practice, to allow OPCUA communication with robots, it's necessary to connect the PC to the same subnet as the robots and, to enable the robot OPCUA server features, ethernet must be connected to the port of the robot controller;

• connection between OPCUA client and server, implemented through the client. Pathway of the serves, IP address of robot controller, port to enable OPCUA communication must be set to effectively establish the communication.

When the connection between robot and PC is effectively implemented, from the client software it is possible to see all the OPCUA variables that can be acquired from the server. There are hundreds of variables available in the internal system of a robot. The next step will consist of the analysis of these variables and understanding which ones are effectively needed to conduct PdM on robots. This connection system can also be useful to acquire some information, not directly related to the PdM, but that ensure the company to better manage the robots.

About stage 3, for the definition of a PdM algorithm, the research team is working on an analysis of the state-of-the-art of available software and tools, considering mainly open source tools (e.g. KNIME Software and Python coding). In particular, the available tools will be classified in relation to their data manipulation models to ensure the reading of datasheets generated by OPCUA software and other instruments already installed in the considered system. This activity is conducted having in mind the features of the Manufacturing Execution System of the company to ensure its communication with the new algorithm. Otherwise a dedicated system will be necessary.

Finally, concerning to stage 4, knowledge and expertise developed in a previous application of augmented reality for automatic packaging machines (Bianchini et al., 2018b) will be transferred to prepare maintenance handbooks (level 2), providing information for operators, who, through wearable devices, are guided in maintenance activities when an intervention is required.

4.Conclusions

A methodology to approach an effective implementation of predictive maintenance on robotic production lines is proposed in this paper. The methodology is under development in a real industrial system, within an Italian Company. The main encountered challenge was related to the availability of data to be acquired and stored, that required the addition of further technology and specific skills on data management. Previous researches often starting from this point, where data are already available, but it is not obvious in industrial contexts. The benefits in the asset management, brought by the implementation of this procedure, are numerous: increased asset availability; better spare part and maintenance staff management and reduction of redundant interventions. All these aspects are also related to an economic benefit. In particular, the additional costs required to implement a PdM strategy and acquire, store, process and visualize maintenance data and information must be compared to the current maintenance contracts with robot producer (about 1700 €/robot per year , which includes annual preventive maintenance and guaranteed intervention in 24h in case of breakdowns), which do not completely avoid plant downtime , therefore it is not possible to plan maintenance interventions in advance with negative consequences on production losses costs. The methodology mainly aims to get in line all the activities that guide a company to shift to a PdM, trying to understand where and how focus the efforts. All the described activities require a strong involvement of human resources (operators, plant and maintenance managers) and, to make the methodology effective, it is necessary to implement a suitable staff training which combines different disciplines (equipment implementation; ITC; data management). Since the approach starts from the basis, the methodology can be easily replicated both in other critical systems in the same company and in other industrial contexts where robotic production lines are widely implemented.

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