Maintenance 4.0: Intelligent and Predictive Maintenance System Architecture

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***Abstract*—In the current manufacturing world, the role of maintenance has been receiving increasingly more attention while companies understand that maintenance, when well performed, can be a strategic factor to achieve the corporate goals. The latest trends of maintenance leans towards the predictive approach, exemplified by the Prognosis and Health Management (PHM) and the Condition-based Maintenance (CBM) techniques. The implementation of such approaches demands a well structured architecture and can be boosted through the use of emergent ICT technologies, namely Internet of Things (IoT), cloud computing, advanced data analytics and augmented reality. Therefore, this paper describes the architecture of an intelligent and predictive maintenance system, aligned with Industry 4.0 principles, that considers advanced and online analysis of the collected data for the earlier detection of the occurrence of possible machine failures, and supports technicians during the maintenance interventions by providing a guided intelligent decision support.**

Keywords: Industry 4.0, industrial maintenance, predictive maintenance, data analysis, augmented reality.

I. Introduction

Throughout the years, the manufacturing world has evolved, forcing all intrinsic and related departments to evolve as well. One of the areas that has evolved significantly is maintenance. Historically, industrial maintenance started as a necessary evil, meaning that maintenance operations were executed only when strictly necessary. However, in industrial manufacturing environments, often characterized as being stochastic, dynamic and chaotic, maintenance is a crucial issue to ensure production efficiency, since the occurrence of unexpected disturbances leads to a degradation of the system performance, causing the loss of productivity and business opportunities, which are crucial roles to achieve competitiveness. In fact, the costs associated to maintenance tasks in a production company are extremely significant, but unfortunately necessary to ensure the required productivity levels. For example, considering a press machine that has short stoppages of five minutes per hour, leading to 40 minutes of downtime per shift (considering a eight hour shift), if we consider that we have a production rate of 14 pieces/minute, at the end of the shift the loss can go up to 560 pieces. Assuming that the machine is producing an exit cone of the catalyst piece for Jaguar, for which the sale price is about 1,26 € per piece, the total loss will be bigger than 705,60 € per shift, since this value does not consider the correspondent maintenance additional cost incurred to recover the equipment.

Nowadays, industrial maintenance is mainly reactive and preventive, being the predictive strategy only applied for critical situations. Traditionally, these maintenance strategies are not taking into consideration the huge amount of data being generated in the shop floor and the available emergent Information and Communications Technology (ICT), e.g., Internet of Things (IoT), Big data, advanced data analytics, cloud computing and augmented reality. However, the maintenance paradigm is changing and industrial maintenance is now understood as a strategical factor and a profit contributor to ensure productivity in industrial systems [1], [2]. This shift in the maintenance paradigm has led to the research and development of new ways to execute maintenance by considering the operational state of assets and enabled the development of new maintenance approaches, such as the Prognostic and Health Management (PHM), the condition-based maintenance (CBM), amongst others [3]. In its broad sense, these approaches apply data analysis techniques to the information produced in the shop floor processes to detect anomalies in the assets' behavior.

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Thus, having in mind the improvement of the performance of the production process, this work aims to develop an intelligent and predictive approach for the industrial maintenance, aligned with the Industry 4.0 principles, that considers advanced analysis of the data collected from the shop floor to monitor and earlier detect the occurrence of disturbances and consequently the need to implement maintenance actions. This approach extends PHM and CBM maintenance approaches by considering machine learning and augmented reality technologies to support maintenance technicians during the maintenance interventions by providing a guided intelligent decision support articulated by the use of human-machine interaction technologies.

The rest of the paper is organized as follows: Section II presents an overview on the most relevant concepts and techniques associated to predictive maintenance. Section III describes the overall architecture for an intelligent and predictive maintenance system. A detailed description of the architecture modules related to the data collection and analysis for monitoring and early identification of maintenance needs is presented in Section IV. Section V describes the decision support system, detailing the module related to the intelligence of the decision support engine and how augmented reality will be used to support the execution of maintenance operations. Finally, Section VII rounds up the paper with the conclusions.

II. Related Work

In modern manufacturing systems, the role of maintenance is becoming more important contributing to the organization profit, clearly bringing the need for the maintenance operation to be in harmony with the corporate objectives [2].

Usually, the maintenance management is categorized into different policies: (i) corrective or run-to-failure maintenance, (ii) preventive maintenance, and (iii) predictive maintenance. Corrective maintenance is an unscheduled repair, where equipments are allowed to operate until they fail, moment in which a maintenance intervention is performed. Preventive maintenance, probably the most popular maintenance policy, is a regularly performed set of actions on an equipment to lessen the likelihood of it failing. This type of maintenance is performed while the equipment is still working and is planned so that any required resources are available. Finally, predictive maintenance is a philosophy or attitude that uses the actual operating condition of the plant equipments and systems to optimize the plant operations and/or processes [4]. Predictive maintenance concerns the application of sensor technology and analytical tools to predict when equipments' failures might occur and to prevent the occurrence of the failures by performing maintenance. The failures' prediction can be done by applying, e.g., vibration monitoring or thermography, and must be effective at predicting failures and also provide sufficient warning time for the upcoming maintenance. When this policy is working effectively, maintenance is only performed on equipments when it is required.

The PHM concept is often used with other approaches like predictive maintenance and CBM [5]. PHM is an engineering process where algorithms are used to detect anomalies, diagnose faults and predict Remaining Useful Lifetime (RUL). Although the main goal of PHM is to provide the health state and estimate the RUL of the components or equipments, also financial benefits such as operational and maintenance cost reductions and extended lifetime are achieved [6]. A PHM analysis involves a variety of steps including the collection of data and data characterization, the extraction of features from collected data, and finally the diagnosis and prognosis. Essential steps for implementing a PHM system are discussed in detail in [7].

According to Alaswad and Xiang [8], CBM is *"a maintenance strategy that collects and assesses real-time information, and recommends maintenance decisions based on the current condition of the system"*. In summary, CBM policies predict the remaining useful life based on the currently observed system state, and suggests system inspection and maintenance actions. Furthermore, it allows end users to perform better-planned maintenance, reduce or eliminate unnecessary inspections, and decrease time-based maintenance intervals with confidence.

There are various international standards related to the CBM approach, for example the ISO 13374 [9] addresses the Open System Architecture for Condition-Based Maintenance (OSA-CBM), held by MIMOSA [10], representing formats and methods for communicating, presenting, and displaying relevant information and data. Initially, OSA-CBM comprised seven generic layers to attain a well constructed system [11], but currently considers six functional blocks [10]:

1) Data Acquisition: provides the access to digitized sensor or transducer data and records this data.
2) Data Manipulation: may perform single and/or multi-channel signal transformations and may apply specialized feature extraction algorithms to the gathered data.
3) State Detection: performs condition monitoring by comparing features against expected values or operational limits and returning conditions indicators and/or alarms.
4) Health Assessment: determines if the system's health is suffering degradation by considering trends in the health history, operational status and maintenance history.
5) Prognostics Assessment: projects the current health state of the asset into the future by considering an estimation of future usage profiles.
6) Advisory Generation: provides recommendations related to maintenance actions and modification of the asset configuration, by considering operational history, current and future mission profiles and resource constraints.

In the OSA-CBM architecture, data flow usually occurs between adjacent functional blocks. Nevertheless, if required, each block may be able to request data from non adjacent functional blocks [11].

In the recent years many efforts have been done in order to implement predictive maintenance in the factories. For example, the *Senseye* company [12] provides a system that gathers data from several sources, analyzes this data and sends a notification to a designated person every time a abnormality is detected or failure is predicted. This solution uses machine learning to perform condition monitoring and prognosis analysis. Other example, is the Watchdog Agent-based Real-time Remote Machinery Prognostics and Health Management (R2MPHM) platform presented and detailed in [13]. The Watchdog Agent consists of embedded computational prognostic algorithms and a software toolbox for predicting degradation of devices and systems. The Watchdog Agent-based R2MPHM platform receives data, processes it and extracts features that allows to detect possible failure occurrence and supports the estimation of the remaining useful life. For this purpose, the Watchdog Agent Toolbox makes use of several techniques and algorithms, such as Neural Networks, Bayesian Belief Network, Fuzzy Logic Prediction.

In spite of the referred benefits, the application of data acquisition, data processing, fault diagnostics, prognostics, and decision reasoning are still not mature enough [14], neither working in an integrated manner. For this reason, companies do not have yet enough trust on these techniques and technologies to implement to handle intelligent and predictive maintenance tasks. Another reason for the lack of implementation is related to the costs associated with integration of an intelligent system with the existing systems as well with the reluctance of change from the human players.

Another key aspect, for this maintenance innovations be fully exploitable, is taking place during the maintenance procedure phase, i.e. when the actual repair actions are taking place. Here, machine learning algorithms allied with augmented reality will have a symbiotic connection aiming to provide an intelligent, interactive, simple and effortless maintenance repair operation. In fact, machine learning algorithms will dynamically guide the maintenance repair technician while the virtual reality environment will provide a comfortable human-system interaction.

III. System Architecture

A proper system architecture for condition-based maintenance should present specific modules such as those described in the previous section. The proposed system architecture integrates all the aforementioned referred modules to create a functional system that allows the implementation of intelligent and predictive maintenance, taking advantage of a broad spectrum of technologies, such as IoT, machine learning, expert systems, among others. The developed architecture is depicted in Figure 1.

The system functionality is initiated with the Data Collection module, where the data from several sources is collected and stored in a database. This database will feed the Off-line Data Analysis module, where advanced data analytics, machine learning and cloud technologies are used to perform the knowledge generation. The outputs of this module are the generation or adjustment of rules, procedures and facts, which will be used by the Dynamic Monitoring functional block.

The Dynamic Monitoring module is divided into two components, the Visualization and the Early Detection of Failures. The Visualization component allows to compare Key Performance Indicators (KPIs) against the expected operational limits. In order to determine these operational limits the facts resultant from the Off-line Data Analysis are considered and the raw data is displayed in a graphic format to facilitate its interpretation. On the other hand, the Early Detection of Failures component processes the facts and rules through the use of an inference engine, and triggers a maintenance warning when an anomaly is detected in an earlier stage. Depending on the detected anomaly, the maintenance warnings can lead to different maintenance actions, namely corrective, preventive or predictive. Once the need for a maintenance intervention is detected, this information is sent to the scheduling tool, that will schedule the intervention according to the current production state and the maintenance resources availabilities. In spite of the importance of the scheduling system, this is out of scope of this work and consequently will not be detailed in this paper.

The execution of scheduled maintenance interventions is guided and supported by a decision support system that selects the appropriate maintenance procedure and translates it into a language understandable by the human. The Intelligent Decision Support module is also able to adapt or create new maintenance procedures in cases that there are no known maintenance procedures for the detected anomaly. The maintenance procedure is provided to the maintenance technician, while performing the required maintenance actions, by using advanced Human-Machine Interfaces (HMI), e.g., head mounted devices.

Comparing the proposed system architecture with the OSA-CBM architecture, it is possible to verify that both present similar functional blocks. The Data Collection module of the proposed architecture is equivalent to the Data Acquisition functional block of the OSA-CBM. Also, the Data Collection module fits, partially, within the Data Manipulation functional block of the OSA-CBM. The Off-line Data Analysis module is aligned with the Data Manipulation and the State Detection functional blocks since the knowledge needed to perform condition monitoring is generated in this module. The Dynamic Monitoring of the proposed architecture matches the State Detection, Health Assessment and Prognosis Assessment functional blocks of the OSA-CBM architecture. The Decision Support module is completely aligned with the Advisory Generation functional block. Figure 2 illustrates how the OSA-CBM architecture was adapted to the Maintenance 4.0 approach.

IV. Data Analysis for Monitoring and Early Identification of Maintenance Needs

This section concerns the Data Collection, Off-line Data Analysis and Dynamic Monitoring modules, which are able to perform the analysis of the collected data to perform the monitoring of the assets' condition and the early detection of failures, and consequently detects the need for maintenance interventions.

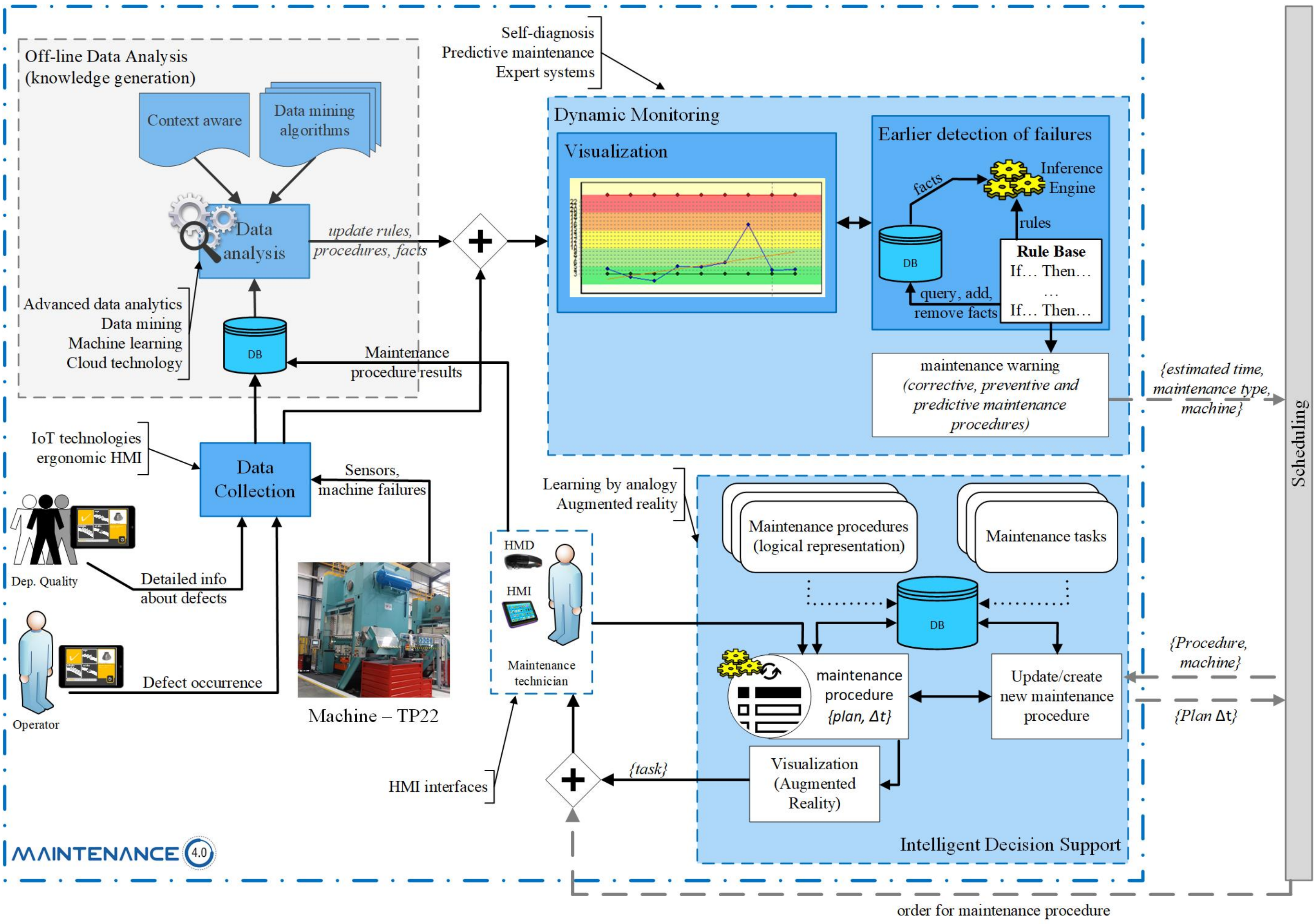

Figure 1. System architecture for the intelligent and predictive maintenance 4.0.

This predictive capability contributes for the reduction of the production process downtime, the optimization in planning the maintenance interventions, and transforms the traditional "fail and recover" practices into "predict and prevent" practices.

A. Interfaces Design for Data Collection

The Data Collection module considers different ways to collect data, namely automatic, semi-automated and manual data collection. The data collection is considered automatic when is automatically acquired and stored in the database that will feed the rest of the system, semi-automatic when the information is automatically recorded in a database but has to be manually transferred to the system's database. Finally, the manual data collection occurs through the use of interfaces, where the information is manually inserted by a worker. Thus, this module can receive information from multiples sources, i.e. from several machines or assets, or from several departments or services. The collection of the required data is performed considering the IoT technologies and the ergonomic standards of HMI.

The design principles, to create user interfaces for data collection in industrial environments, should always take into consideration relevant features, such as the information presentation and the type of interface. The overall effects of the HMI appliance could not be totally predictable or even measurable since they do not depend only on the system design. The design goals and the consequent application should take into account the hierarchy of needs, such as 1) substantial procedures and advices, 2) continuous performance efficiency checklist, 3) ratings that come from data assessments, 4) specifications concerning reliability and validity, and 5) usability and efficacy of the system.

HMIs should be designed to involve users in the definition of the display and customization of the right assistance by applying the User Centered Design approach [15]. Also, the user interfaces must follow ergonomic guidelines established for the well-design of software and hardware systems. The following guidelines are some examples of the broad spectrum of guidelines that must the considered for the interfaces design:

- The interface should never give rise to potentially hazardous behavior for the user (ISO 4040).
- The place of the system should never damage the user responsiveness and must remain compatible with the hierarchy of attention demand, e.g., closeness, line of

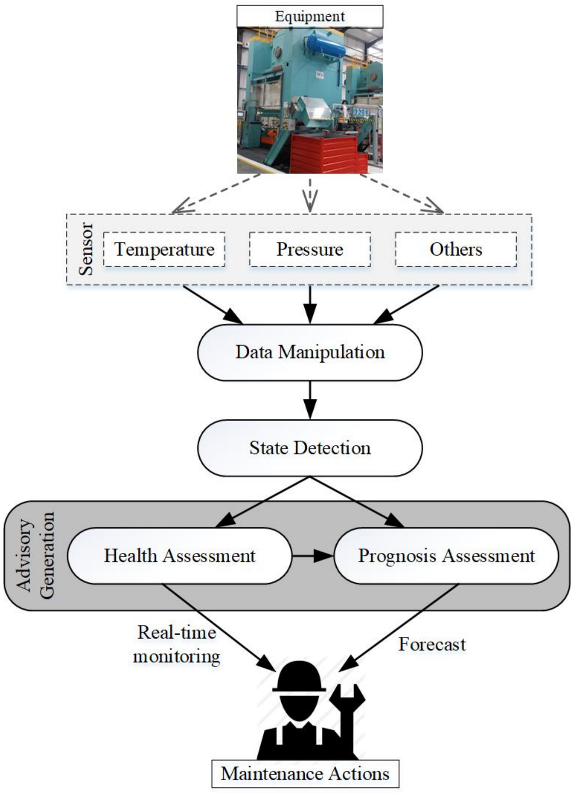

Figure 2. Adaptation of the interaction between the functional blocks of the OSA-CBM for the Maintenance 4.0 project.

sight and comfortable position.

- The interface should be simple and intuitive, simplifying to understand the information and allowing to be focused in the execution of other tasks, e.g., visual inspection.
- The interaction should consider the ergonomic performance of the user dialogue commutation - range of movement, point-click movement, controls obstruction and display.
- The developed menus should always consider simple structures that promote grouping guidelines of functions to give good 'visuality' to the interaction system.
- The total alignment dialogue trough all elements regarding visual accuracy, aesthetic, and order should have a proper language that will not compromise performance.

Considering the case study considered in this work, that is related to an industrial metal stamping machine producing components for the automotive industry, this module receives inputs from several sources, namely from a stamping machine, operators and the quality department. The information received from the machine consists of a buffer that registers the actions of the machine including the failures occurred, and the information related to some sensors. Regarding the operator, the information collected refers to the defect occurrence and is collected through the use of a simple and intuitive interface that registers the type of defect detected and the time of occurrence.

Collecting non-automated information during the production process is a complex process, since the operator will have a new focus of attention. The type of information to be collected would be the classification of the defects (and the corresponding timestamp) of the components produced, marked at the end of the production line, when manually inspected one by one. Hand-held devices, such as tablets interfaces, will assist workers during the quality inspection procedure to the task of data collection in real time production, and also by specialists from the quality department, in a subsequent statistical analysis of the data collected. The layout of the developed interface app for the manual data collection is depicted in Figure 3, and operates as a bridge between human intentions and interactions to collect important data so that they can be stored and available in a real time automatic system machine.

Figure 3. User interface for the defects' data collection.

In a technological perspective, HTML, AngularJS, PHP and CSS were used to guarantee portability and transversality of the application in different mobile operating systems, as well as the web connection to collect and record data in real time, as illustrated in Figure 4. HTML and CSS were used to configure the appearance of the several interface elements to be displayed on a web page of any browser. AngularJS was essential in the application of dynamic functions, so that all data was shown to the operator automatically, and updated in real time. PHP, as a server language, established the connection between the web interface and the database, allowing to send and receive information.

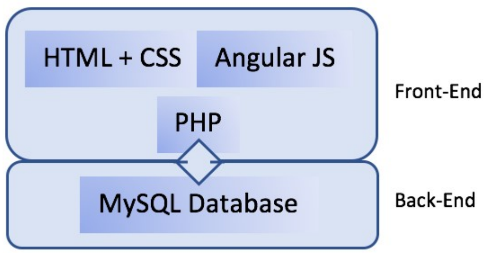

Figure 4. Architecture of the app for the collection of data related to defects.

After the conceptual analysis of the involved information flow, the related set of classes were defined to store the elemental information to the collection of data structures.

The class entities resulting from the conceptual model are presented in the Database, and related to the registration of the information concerning Operators, Defects, Production Batches and the respective evaluated Produced Pieces. All this information is collected, interconnected, and stored in a MySQL database, communicating with the interface page through SQL commands present in PHP.

This type of information, associated to the defects and timestamps signaled by the workers at the end of the assembly line during the inspection task, will be presented in real time to the quality department. In the quality department, with the help of a tablet with a dashboard interface, real-time statistical information will be updated from the data collected to predict future changes in quality of pieces at the production lines.

B. Off-line Data Analysis

This module will take advantage of several technologies, namely advanced data analytics, machine learning and cloud technologies to extract knowledge from the collected data in order to create new monitoring rules and procedures or update the existing ones. For this purpose, a deep machine learning approach with supervised learning for the early fault prediction and predictive maintenance was developed. The algorithm was trained from the input data of previous events/faults, labeled accordingly to the type of event (fault or operation), rather than being explicitly programmed by a set of static rules. Due to the large dataset (more than 43000 events from 10 working days), the deep machine learning approach has the advantage of detecting underling patterns that may not be detected by a human operator/programmer [16], [17].

The evaluation of this machine learning approach was tested on two types of recurrent neural networks (RNN), the long short-term memory (LSTM) and the gated recurrent unit (GRU) [18]. These networks are especially attractive to the predictive maintenance domain since they can learn from past sequences and forecast the next probable event. The input data consists in more than 43000 previous events, each of which is represented by a preprocessed encoded feature vector that encodes the event type (e.g. sensor activation, axis error, missing parts, etc.), the day of week, the time of day (in 5 min blocks) and the time from a past event, in a total of 147 features. The data was separated into a training and validation set and a testing set by 70% and 30%, respectively.

The overall model architecture, represented in Figure 5, consists in a LSTM/GRU layer feed with all sequences of events through each internal layer, the final LSTM state encodes the machine behavior, including relations between past and recent events. The final LSTM state is then input in a fully connected output layer which determines the probability of a specific fault type in the next 5 minutes block. Training was accomplished using an LSTM network with 200 cells, Adam optimizer and binary cross entropy as loss function through 50 epoch.

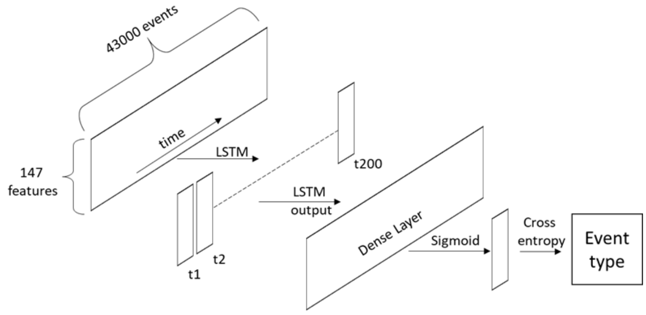

Figure 5. Proposed RNN model architecture based on a LSTM layer to predict the next failure/event type.

C. Dynamic Monitoring

The Dynamic Monitoring module comprises two components, the Visualization and the Early Detection of Failures.

The Visualization receives inputs from the Off-line Data Analysis module that provides information about the normal functioning of assets operational limits, and data from the Data Collection module, which allows a real-time monitoring of specific variables. The real-time parameters will be graphically represented in a chart and when a parameter exits its operational interval, or the trend shows that it will eventually exit its operational interval, the data point is labeled in the graphical interface. Some examples of the parameters that will be visualized are described in Table I.

Table I
EXAMPLE OF COLLECTED DATA PARAMETERS.

Parameter	Description
Type of defect	Type of defect detected while the visual inspection is performed
Date	Date and time when the defect is detected
Part reference	Identification of the part where the defect is detected
Pressure	Pressure of the hydraulic piston during the operation
Temperature	Temperature in the surroundings of the equipment
Humidity	Humidity in the surroundings of the equipment
Vibration	Vibration of some components of the equipment
Operational noise	Characteristic noise produced during the operation of the equipment

On the other hand, the Early Detection of Failures is performed by a inference engine that uses a set of rules to match the existing facts, which can be retrieved from the database where the collected data is being stored. The rules are generated in the Off-line Data Analysis module through the detection of the correlation between different parameters. The rules follow a simple structure based on the `If Condition then Action` syntax, which are processed by the inference engine. When a rule is fired, a correspondent action is triggered, namely a warning for the need of maintenance interventions.

Both Visualization and Early Detection of Failure components may exchange data.

When the need for maintenance interventions is detected, the information is sent to the Decision Support module through the scheduling tool.

V. Intelligent Decision Support for Maintenance Interventions

An important piece in this intelligent and predictive maintenance architecture is the decision support system for maintenance technicians during the execution of maintenance interventions. This intelligent decision support system, articulated with human-machine interaction technologies, e.g. augmented reality, contributes for a faster and more efficient reaction and recovery of the failure occurrence when compared to paper procedures [19].

A. Intelligence of decision support engine

The Intelligent Decision Support module is composed by a database, which can be shared by the database used in the other modules, an engine that processes the maintenance procedures, a tool that allows to update or create maintenance procedures and a human-machine visualization tool.

The database contains, amongst others, the maintenance procedures expressed in a formal logical representation, e.g., BPMN (Business Process Model and Notation) as the example depicted in Figure 6, which defines the sequences of single maintenance tasks. This database is connected to an inference engine that selects the proper maintenance procedure, and translates the procedure into a language understandable by the human that will be applied in the maintenance intervention.

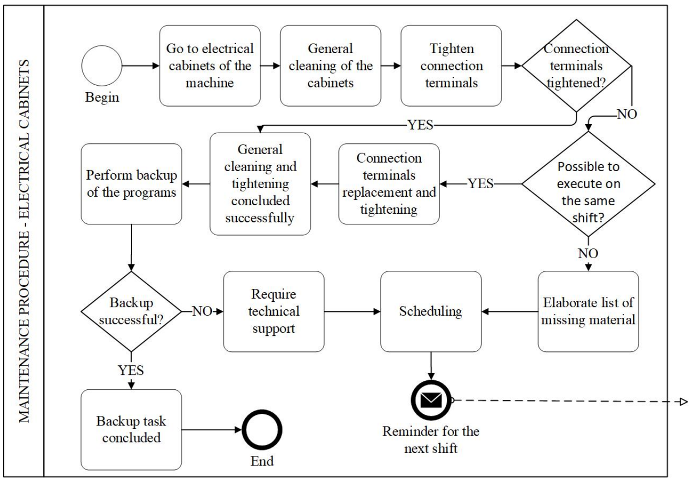

Figure 6. Example of a maintenance procedure expressed in BPMN format.

For each case, if the necessary maintenance intervention does not have a correspondent maintenance procedure in the database, the engine enriched with machine learning, and particularly learning by analogy algorithms, will attempt to adapt or create a new maintenance procedure. This means that the engine will search for maintenance procedures applied to failures with similar features and show it to the operator.

B. Augmented reality to support interactive maintenance operations

Augmented Reality (AR) is not a new technology, but instead it has been an active research area since almost three decades. AR is an interesting technology as it enhances the user's interaction and the perception of the real world by supplementing it with virtual things that coexist in the same space as the real ones. Therefore, AR supplements reality, rather than replacing it [20], [21]. Recent interest is being driven by enhancements of graphics capabilities, in particular in mobile and wearable devices, and in the plentifulness of wide assortment of sensors and, as well as, the support of advances on tracking combined with the availability of affordable AR enabled hardware, such as Microsoft HoloLens [22], DAQRI smart glasses [23] or Atheer AiR Glasses, made AR an emergent topic of applied research.

All of this is also supported by the growth in the number of things with a virtual counterpart. Information (3D models and animations, real time information, documentation, etc.) regarding every thing with a virtual/digital existence, feeds applications that can supplement the user with a multitude of relevant, up-to-date and contextualized knowledge. Thus, AR technologies are interesting to many sectors, including industrial applications, from design through maintenance processes.

Since its origination, several AR applications have been envisioned and conceived to the manufacturing sector, such as assembly, maintenance, and repair of machinery [20], [21], [24], [25]. There have been several systems demonstrating the ability and usefulness of AR to act as an instruction and guidance tool [26]. Recently, the AR adoption by key players on industrial innovation, such as Boeing and General Electrics, resulted in the following main benefits: improved productivity, higher product and process quality (decreasing error rates), and better ergonomics.

This augmented reality component is being implemented with a hololens head mounted display and a tablet display. In both cases, the operator sees the real scene (the machinery) and sees the maintenance operation augmented over the real scene. The first offers an immersive experience where the interaction is done with hand movements to make selections. The second follows a traditional approach through the tablet display and the interaction is achieved through touch. The task is entrusted to a operator that follows the instructions presented on the AR display. In a first approach the system will be aimed for the operator training.

Each maintenance operation has several steps to follow in order to successfully achieve the task. The augmented reality process is supported by text, audio and 3D models and animations. The text describes the operation step together with an audio description which can be controlled during the process. The 3D models and animations represent the machinery and explains the operation with a 3D animation of the process to be done. It may assume that pieces are involved in the maintenance process, in which case, they are identified by its 3D model and factory reference.

At each maintenance step, the operator must confirm its completion before continuing, by interacting with the display interface. The interface includes buttons to confirm steps, to retrieve steps, to cancel the whole operation or to open a communication channel with a senior operator. The operator may be assisted by a more experienced operator during the maintenance process. For such purpose, the operator may start a video or audio conference with an assistant to make any questions concerning doubts or problems one may have during the maintenance process.

VI. Conclusion

Nowadays maintenance is considered as an integral part of the manufacturing process that contributes to the product quality, plant availability and ability to meet delivery schedules. This is particularly important in manufacturing companies that adopt modern management philosophies. The growing importance of maintenance management has generated an increasing interest in the development and implementation of efficient maintenance strategies that are able to improve the system reliability, prevent system failures, and reduce maintenance costs.

In this context, predictive maintenance policies, together with, e.g., PHM and CBM approaches for maintenance management, can be considered important tools to industries in the era of emerging ICTs. This paper introduces the architecture of an intelligent and predictive maintenance system, aligned with Industry 4.0 principles and following the structure of functional blocks of the OSA-CBM. This system architecture considers advanced and online analysis of the collected data for the earlier detection of the occurrence of possible machine failures, and supports technicians during the maintenance interventions by providing a guided intelligent decision support. The proposed system extends the basic CBM functionalities with the integration of decision support systems and augmented reality technologies to enhance the interaction among humans and machines, improving the performance of the execution of maintenance interventions.

Future work will be devoted to the further development of the several system architecture modules, and the posterior deployment in a real industrial production unit focusing the metal stamping for the automotive sector.

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