Deployment of a Smart and Predictive Maintenance System in an Industrial Case Study

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***Abstract*—Industrial manufacturing environments are often characterized as being stochastic, dynamic and chaotic, being crucial the implementation of proper maintenance strategies to ensure the production efficiency, since the machines' breakdown leads to a degradation of the system performance, causing the loss of productivity and business opportunities. In this context, the use of emergent ICT technologies, such as Internet of Things (IoT), machine learning and augmented reality, allows to develop smart and predictive maintenance systems, contributing for the reduction of unplanned machines' downtime by predicting possible failures and recovering faster when they occur. This paper describes the deployment of a smart and predictive maintenance system in an industrial case study, that considers IoT and machine learning technologies to support the online and real-time data collection and analysis for the earlier detection of machine failures, allowing the visualization, monitoring and schedule of maintenance interventions to mitigate the occurrence of such failures. The deployed system also integrates machine learning and augmented reality technologies to support the technicians during the execution of maintenance interventions.**

***Index Terms*—Industrial maintenance, Predictive maintenance, Intelligent Decision Support, Augmented reality.**

I. Introduction

In industrial manufacturing environments, often characterized as being stochastic, dynamic and chaotic, maintenance systems are crucial to ensure the 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 [1]. Traditionally, industrial maintenance is mainly reactive and preventive, being the predictive strategy only applied for critical situations. 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 [2], [3], with predictive maintenance assuming a crucial role. Predictive maintenance involves the collection and evaluation of data from machines to increase efficiency and optimization of the maintenance processes [4], considering advanced techniques, e.g., sensor technology and analytical methods, to predict when equipment's failures might occur and to prevent the occurrence of the failures data by performing maintenance [5].

In this context, new maintenance approaches are enabled by considering the operational state of assets, such as the Prognostic and Health Management (PHM), the Condition-Based Maintenance (CBM) and even Digital Twin [6]. CBM is a maintenance strategy that uses the collected real-time data to determine the machine's condition and predict the need for maintenance actions [7]. Furthermore, it allows a more optimized planning, reducing the unnecessary interventions and the time-based maintenance intervals with confidence.

The Industry 4.0 advent has created an opportunity for predictive maintenance, by considerating the huge amount of data being generated on the shop floor and the available emergent Information and Communication Technologies (ICT), e.g., Internet of Things (IoT), Big data, machine learning and cloud computing. The consideration of artificial intelligence and new human-machine interfaces, e.g., virtual and augmented reality technologies, also allows to develop smart decision support systems that help technicians to execute maintenance interventions, contributing to reduce the maintenance costs and the machines' downtime. In spite of the significant work implemented as lab prototypes, few industrial implementations are reported in the literature, e.g., using big data to predict the remaining life of a key component of a machining equipment [8] and data mining to perform fault diagnosis and prognosis in machine centers [9]. In the same manner, augmented reality is supporting human workers in a rapidly changing production environment, e.g., assembly of new products, maintenance staff and plant planner [10], or supporting the better understanding of assembly procedures [11].

Having this in mind, a smart and predictive maintenance system is deployed in an industrial metal stamping machine, considering an online analysis of the collected data to monitor and earlier detect the occurrence of failures, transforming the traditional "fail and recover" practices into "predict and prevent" practices. This approach also considers an intelligent decision support system that assists the technicians during the

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execution of the maintenance interventions, contributing for a faster and more efficient recovery of the failure occurrence.

The rest of the paper is organized as follows: Section II overviews the smart and predictive maintenance system architecture, and Section III describes the deployment of the data collection and data analysis applications for the industrial metallic stamping case study aiming the dynamic monitoring, and particularly the earlier detection of machine's failures. Section IV presents the developed intelligent decision support application using augmented reality technology to support the technicians during the execution of maintenance interventions. Finally, Section V rounds up the paper with the conclusions.

II. System Architecture

The proposed system architecture for the condition-based maintenance takes advantage of a broad spectrum of emergent technologies, such as IoT, machine learning and augmented reality, and comprises several modules, namely the data collection, the analysis and monitoring, and the intelligent decision support (IDS), as illustrated in Figure 1 [1].

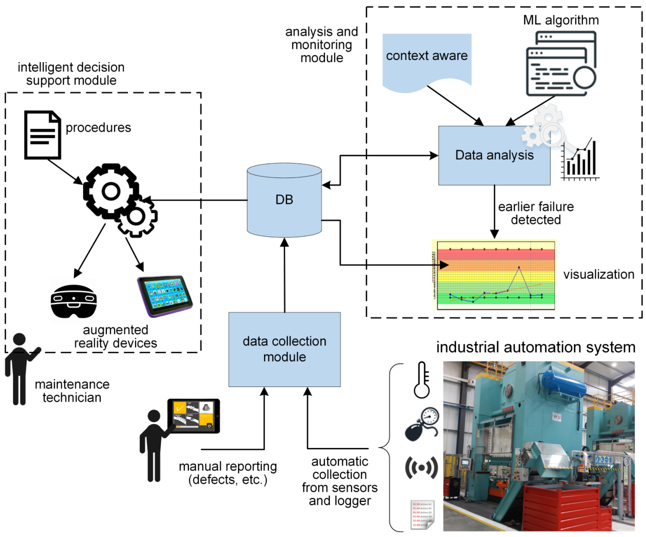

Figure 1. Smart and predictive maintenance system architecture.

Briefly, the data collection module is responsible for the manual and automatic collection of data from several heterogeneous sources, using IoT technologies. The collected data, stored in a database, will feed the analysis and monitoring module that is responsible for the monitoring of the machine health along the time but also the earlier detection of machine failures (i.e. the needs for maintenance interventions). For this purpose, data is continuously analysed and correlated using machine learning techniques. Finally, the intelligent decision support module is responsible to support the technician during the execution of maintenance interventions, providing guidance and easy access to the machine condition through the use of augmented reality technologies.

The proposed system architecture was implemented in an industrial case study comprising a metallic stamping machine that stamps metal parts with 400 tons of force and operates in a range of 10 to 24 strikes per minute. This machine is composed by a storing system, a feeding system and a transfer system that transfers the parts through the successive stamping stations. These systems operate synchronously through the use of a Siemens S7 PLC (Programmable Logic Controller) alongside with several Sinamics motor controllers. At the end of the stamping process, an operator is responsible to execute the visual inspection of each produced part, which data is not currently recorded.

III. Dynamic Monitoring and Prediction

This section details the implementation of the data collection and analysis methods to support the dynamic monitoring, including the earlier detection of failures.

A. Automatic Data Collection using IoT

The automatic data collection module allows to gather several operational and environmental parameters, namely atmospheric pressure, temperature, humidity, hydraulic pressure and vibration, reflecting the condition of the machine. For this purpose, several sensing modules were developed and installed strategically in the machine, without damaging or impairing its proper operation, as illustrated in Figure 2.

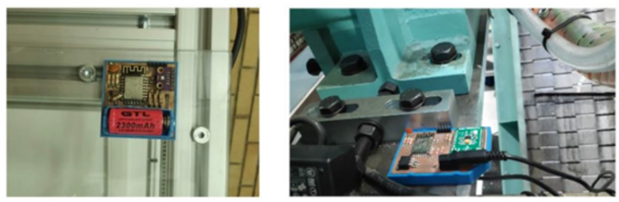

Figure 2. Sensing modules installed in the metal stamping machine.

The operational data (right side of Figure 2), e.g. the vibration, is collected at 300 samples per second, but the environmental data (left side of Figure 2) is collected each 5 minutes, since they do not suffer significant changes in short periods of time. These sensing modules constitute IoT nodes capable to acquire and transmit these parameters over Wi-Fi, following a JSON file format. The transmission protocol is the Message Queue Telemetry Transport (MQTT), that uses the publish/subscribe schema and a message protocol optimized for TCP/IP. The collected environmental and operational data, as well as the log of warnings and failures generated by the machine, are stored in a database.

The autonomy of these sensing modules is improved by integrating a controlled switch in the power circuit, allowing the temporary power-off of all components, with the exception of the micro-controller which is kept in deep-sleep mode, when the module is not acquiring or transmitting data.

B. Manual Data Collection

The data regarding the products' defects is manually collected from operators by using a friendly and ergonomic user interface (UI), as illustrated in Figure 3.

In this web-based application, running in a hand-held device, e.g. a tablet, the operator can report a part defect by

Figure 3. UI for the defects' data collection.

selecting the product being produced and the defect that should be reported. The data associated to the defect, including the part type, the defect type and the timestamp, is stored in the database, and visualized in real-time.

C. Visualization and Dynamic Monitoring

The collected data is only useful if analysed, allowing to monitor the machine's condition and the products' quality, detect in advance failures and trigger maintenance interventions to mitigate the degradation of the machine performance. For this purpose, the acquired data is monitored through a computational application developed in the Node-RED platform (https://nodered.org). The first dashboard, depicted in Figure 4, was built on the top of a responsive framework enabling its dynamic adaptation according to the hosted device, and is related to the real-time visualization over the time of the environmental and operational parameters, collected by the developed IoT nodes. The dashboard also shows warning messages as a result of applying process control methods, particularly Nelson rules [12] that use the mean value and the standard deviation to determine if a parameter is out of control or presents a trend towards to be out of control. Besides the monitoring in the dashboard, these warnings are sent by email or SMS to the maintenance manager.

A second dashboard, illustrated in Figure 5, provides statistical information regarding the product quality (i.e. product defects) and the machine operation (i.e. machine failures). Regarding the products quality, the dashboard displays for each type of defect, the total number of occurrences, the date of the last occurrence, the time without defect (in days) and the Mean Time Between Failure (MTBF), which is a crucial industry parameter to be considered. The same display schema is used to monitor the machine health parameters, considering the data regarding to the machine failures. This dashboard also provides the visualization of the real-time events regarding to the product defects and machine failures.

As a Web-based UI, the maintenance technician can remotely access the complete Node-RED monitoring application, allowing to monitor the current condition of a given asset (in terms of product or machine failures and warnings). For this purpose, the technician can connect with a mobile phone to the network where the dashboard is housed, either by WiFi or VPN, and access via the dashboard's IP.

D. Prediction of Machine's Failures

A machine learning approach with supervised learning was implemented for the early prediction of failure occurrences, concerning the advantage of detecting underling patterns that may not be detected by a human operator/programmer [13], [14]. For this purpose, the early failure/warning prediction inference engine was codified in python and uses a type of recurrent neural networks (RNN), the LSTM (Long Short-Term Memory) network [15]–[17], which is especially attractive to learn from past sequences and forecast the next probable event. The implemented network was configured with 50 up to 150 cells, the Adam optimizer and binary cross entropy as loss function through 30 epochs. The algorithm was trained using as input data the previous events collected from the log of machine failures (more than 43.000) using the csv format, classified and labeled accordingly to the type of event (failure as 1 or warning as 0), rather than being explicitly programmed and harmonized by a set of static rules. Since the majority of the events are not related to failures, i.e. almost 98% of the original machine events are warnings, resulting in extremely imbalanced dataset, the model was designed to group events in 5 minutes blocks and thus predict the type of event that may arise in the next 5 minutes (failure or not).

Figure 6 represents the results for the training and validation accuracy and loss for the 150 neuron configuration and considering the range up to 30 epochs. The results show an increase in the accuracy with a steady decrease in loss, reaching a value of 99% accuracy after 15 epochs, which suggests that the network is able to properly learn patterns or new features.

The implemented prediction algorithm was able to predict anomalies from internal and external data sources. However, the restrictions in the access to internal machine data restricted the prediction time range to 5 minutes. The predicted failure or warning occurrences were real-time represented in the bottom of the dashboard illustrated in Figure 5, which shows the probability of the failure occurrence and the type of failure. Additionally, on the right side of the dashboard are indicated which failures or warnings are most likely to be predicted.

IV. Intelligent Maintenance Assistance

The IDS module is responsible to provide guidance to the technician to execute the maintenance interventions in a faster and more efficient manner, showing the way to execute the sequence of actions using text, images, videos and/or 3D animations, and accessing to the historical and current data regarding the machine operation. This module comprises two distinct applications with interactive UIs: the first application was developed to run in an Android environment for a regular operational usage, while the second application was developed for training, under the Microsoft HoloLens environment.

A. IDS for Android Environment

The IDS application developed for the Android environment comprises three modules: Maintenance procedures, Training and Monitoring. The first module provides a guidance through the execution of maintenance procedures, showing to the

Figure 4. Visualization and monitoring of machine's parameters along the time.

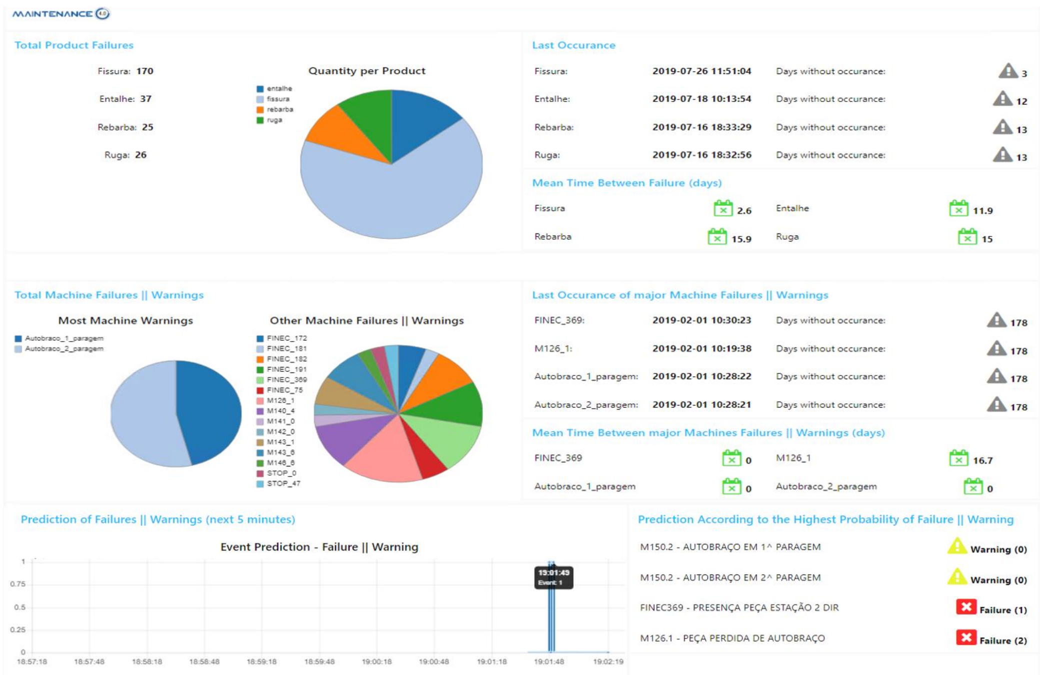

Figure 5. Visualization and monitoring of statistical data related to product's defects and machine's failures.

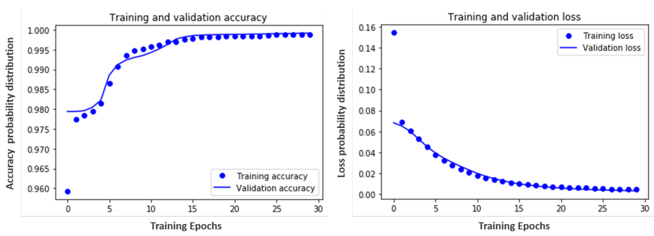

Figure 6. Training and validation accuracy and loss for 150 neurons.

technician a step-by-step sequence of the tasks, explaining the procedure to be executed. Note that each maintenance procedure comprises a sequence of specific tasks that are necessary to be executed by the technician during the maintenance intervention. The maintenance procedures were represented using the Business Process Model and Notation (BPMN) language, which represents the workflow of tasks (see Figure 7). These BPMN chart flows are automatically translated into a XML programmable script by using the Camunda tool. The sequence of tasks, expressed in the XML format, is managed by an engine that is codified in C# using the Visual Studio platform and embedded in the Unity development platform, which provides a flexible and adaptive environment to develop the interface for the Android platform. The engine may associate media files, such as images and videos, to each task step in order to improve the maintenance procedure understanding.

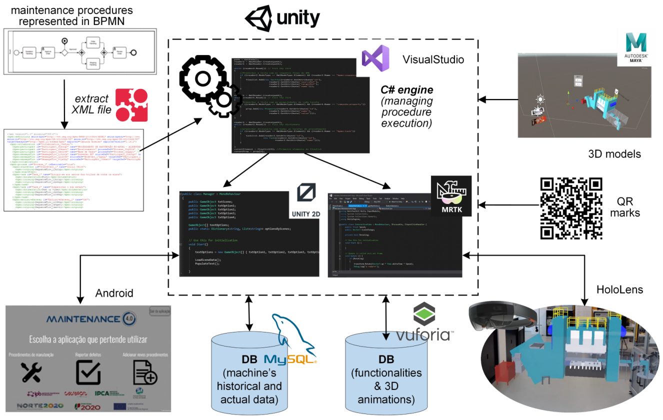

Figure 7. Managing the execution of the maintenance procedures in the Unity environment (for Android and HoloLens platforms).

The existence of a large and diverse number of maintenance procedures can be difficult for the maintenance technician, especially in case of new or complex ones. Having this in mind, the second module, called Training, allows the maintenance technician to train on how to perform the procedures, gaining experience off-line and before to execute the procedure in reality, increasing his performance and efficiency. During each training procedure, there are instructions with video clips detailing the maintenance intervention or sequence of images with detailed explanation of the actions to be taken.

Along the execution of a maintenance intervention, the maintenance technician may require to get information about the machine's condition, in order to decide the actions to be performed. For this purpose, the Monitoring module allows to display the required information by scanning, e.g., using the camera of the tablet, an identification QR mark that is attached to each machine (see Figure 8).

Figure 8. Monitoring the machine condition health.

After identifying the mark, the use of augmented reality technology through Vuforia allows to augment a certain object or display the visualization and monitoring dashboard containing the real-time information about the machine condition state (as described previously in Figures 4 and 5).

During the IDS life-cycle, the data regarding the usage of the tool by the technician is recorded, namely the executed maintenance procedures, the timestamps about the beginning and the end of the executed procedures, and the feedback from the technician during the execution of the maintenance procedure. The collected data will support posterior data analysis related to the technician performance and the average time to execute the maintenance interventions.

B. IDS for HoloLens

As the Unity environment supports the Android and Microsoft operating systems, the application for HoloLens is based on the one for Android with small changes (also shown in Figure 7). The main differences are related to the use of 3D models and gestures and voice commands.

The benefits to creating intelligent maintenance systems as a augmented reality application are mainly the capability to train technicians and operators to work with various equipment without the need to have the training models, and to guide step by step the technician during the execution of the tasks.

The interaction with the HoloLens headset is performed through the Gaze, Gesture and Voice (GGV) paradigm, which means that the headset is able to recognize the users speech, gestures and gaze. With the GGV paradigm, it is possible to select and manipulate virtual objects, for example zooming-in and zooming-out (note that to select an object, the user needs to look at it and give a voice command or tap with a finger, which is equivalent to a click).

Using the Mixed reality Toolkit (MRTK), provided by Microsoft, it was possible to create a list of GGV commands to personalize the control of the application. Figure 9 illustrates the use of the augmented reality application running on a HoloLens at the shop floor.

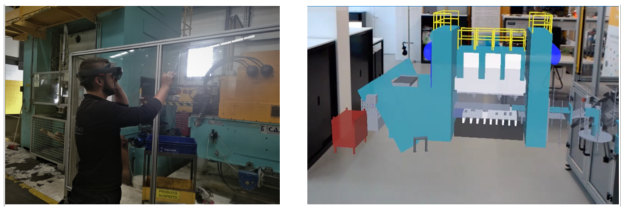

Figure 9. Augmented reality technology applied to maintenance using a HoloLens device.

C. User Experience Evaluation

The developed IDS applications were deployed in the industrial case study, and used by operators in their normal operation, allowing to evaluate the user experience. For this purpose, the System Usability Scale (SUS) survey [18] was used to test the system reliability right after giving the respondent an opportunity to evaluate the system. It consists of a 10-item questionnaire, illustrated in Table I, with a five-level Likert scale [19] with options ranging from "Strongly disagree" to "Strongly agree", with a numerical correspondence from 1 to 5. It is a mixed-tone questionnaire in which items have alternatively a positive and a negative tone. For positive items the score contribution is the scale position minus 1, and 5 minus the scale position for the remaining. By multiplying the sum of the scores by 2.5, the overall value of SUS is obtained. The SUS score reflects a measurement of the system reliability with its own assessment concerning the system approval and usually referred as percentiles (in opposition to percentage). A score above 70 is acceptable and between 80 and 90 is considered excellent.

Table I
SUS 10 ITEM QUESTIONNAIRE

I think that I would like to use this system frequently
I found the system unnecessary complex
I think the system was easy to use
I would need the support of a technical person to be able to use the system
I found the various functions in the system were well integrated
I thought there was too much inconsistency in the system
I would imagine that most people would learn to use the system very quickly
I found the system very cumbersome to use
I felt very confident using the system
I needed to learn a lot of things before I could use the system

The performed SUS survey obtained a score of 84.8 percentiles, corresponding to a qualitative evaluation of "Excellent", which means that in general the users had a positive experience. In fact, users highlighted positively the easy to use, the integration of useful functions, the fast learning of the system and the confidence to use the system. However, it is also noticed that the users refer the need to learn more before taking complete advantage of using the system, as well as the discommodity of using the HoloLens devices for long periods, especially due to their weight, which suggests that they should only be used for short periods.

V. CONCLUSIONS

This paper describes the deployment of a smart and predictive maintenance system for an industrial stamping machine case study, that integrates IoT, AI and augmented reality technologies to minimize the effects and impact of unexpected failures in the production system, and consequently increasing the competitiveness of manufacturing enterprises. This is particularly important in manufacturing companies that aim to improve the system efficiency and reliability, by preventing the system failures and reducing the maintenance costs.

The proposed approach considers advanced and online analysis of the collected data for the earlier detection of machine failures and the dynamic monitoring of the machine's condition and products' quality, as well as an intelligent decision support to guide technicians during the execution of maintenance interventions. The deployed solution takes advantage of emergent technologies associated to Industry 4.0, namely IoT, machine learning and augmented reality technologies. Although, several limitations still exist either due to data availability, process digitalization or technician learning curve, particularly in using augmented reality technologies, this work enabled the deployment and validation of the smart and predictive maintenance system in a real industrial production unit for metal stamping for the automotive sector. Future work will be devoted to extend the collection of more internal machine parameters that will allow to predict machine failures with a higher accuracy and earlier, i.e. with a tie range higher than 5 minutes.

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