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EXPERIENCES IN DEVELOPING PREDICTIVE MAINTENANCE SOLUTIONS

EXPERIENCIAS EN EL DESARROLLO DE SOLUCIONES BASADAS EN EL MATENIMIENTO PREDICTIVO

Filipe ALVES[1], Jorge MEIRA[2], Goreti MARREIROS[2], and Paulo LEITAO[1]

[1] *Research Centre in Digitalization and Intelligent Robotics (CeDRI), Instituto Politécnico de Bragança, Campus de Santa Apolónia, 5300-253 Bragança, Portugal*
{filipealves, pleitao}@ipb.pt

[2] *GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, Institute of Engineering, Polytechnic of Porto, 4200-072 Porto, Portugal*
{janme, mgt}@isep.ipp.pt

ABSTRACT: In industrial manufacturing environments, a regular maintenance is 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. In this context, the purpose of predictive maintenance has been receiving increasingly more attention, which when well performed, can be a strategic factor in achieving corporate goals. The predictive maintenance, framed as an important issue in Industry 4.0, is able to anticipate problems or emergencies before they happen, bringing huge advantages to industries that allow them to optimize their results and obtain greater efficiency and profitability of equipment. For that reason, more and more Companies are understanding that the equipment conservation and conditionbased maintenance can contribute to increase their competitiveness. This paper focuses on the topic of predictive maintenance, its benefits, applications and challenges, complemented with the description of predictive maintenance applications, illustrated with two examples of real-world applications resulting from the experiences of the Instituto Superior de Engenharia do Porto (ISEP) and the Instituto Politécnico de Bragança (IPB) in previous R&D projects.

Keywords: predictive maintenance; industrial maintenance; advanced data analysis.

Resumen: En los entornos de fabricación industrial, el mantenimiento es crucial para garantizar la eficiencia de la producción, ya que la aparición de perturbaciones inesperadas conduce a una degradación del rendimiento del sistema provocando la pérdida de productividad y de oportunidades de negocio. En este contexto el propósito del mantenimiento predictivo ha recibido cada vez más atención, que cuando es bien realizado, puede ser un factor estratégico para alcanzar objetivos corporativos. El mantenimiento predictivo, enmarcado como una cuestión importante en la Industria 4.0, es capaz de anticiparse a los problemas o emergencias antes de que ocurran, aportando enormes ventajas a las industrias que les permiten optimizar sus resultados y obtener una mayor eficiencia y rentabilidad de los equipos. Por ello, cada vez son más las empresas que entienden que el equipo de conservación y el mantenimiento basado en la condición pueden contribuir a aumentar su competitividad. Este documento se centra en el mantenimiento predictivo, sus beneficios, aplicaciones y retos, complementado con la descripción de las aplicaciones de mantenimiento predictivo, ilustradas con dos ejemplos de aplicaciones del mundo real reales resultantes de las experiencias del Instituto Superior de Engenharia do Porto (ISEP) y del Instituto Politécnico de Bragança (IPB) en anteriores proyectos de I+D.

Palabras clave: mantenimiento predictivo; mantenimiento industrial; análisis avanzado de datos.

1 Introduction

Nowadays, industrial maintenance is mainly reactive and preventive, being the predictive strategy only applied for critical situations [22]. Traditionally, these maintenance strategies are not taking into consideration 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, advanced data analytics and cloud computing. However, the maintenance paradigm is changing and industrial maintenance is now understood as a strategical factor and a profit contributor to ensuring productivity in industrial systems [9, 17]. This shift in the maintenance 4.0 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, predictive maintenance (PM) to improve system reliability [19], the Prognostic and Health Management (PHM), the condition-based maintenance (CBM), amongst others [11].

In this sense and considering problematic situations resulting from the manufacturing operation and stability are usually hard to detect, and contribute, in a critical manner, to the reduction of Overall Equipment Effectiveness (OEE), this work aims to report the development of predictive maintenance applications, illustrated with two examples resulting from the participation and experiences in industrial maintenance projects by ISEP and IPB. For this purpose, approaches and architectures with advanced data analysis support for monitoring the «machine» health status and the early detection of possible emergencies to mitigate the occurrence of such problems are exemplified.

The rest of the paper is organized as follows: Section 2 overviews the concept of predictive maintenance and Sections 3 and 4 describes two examples of developed predictive maintenance solutions. Finally, Section 5 rounds up the paper with the conclusions.

2 Predictive Maintenance

Predictive maintenance applications predict failure sufficiently ahead of time so that decision makers can take appropriate actions such as maintenance, replacement or even a planned shutdown [15]. These applications facilitate savings on machine maintenance and increase productivity by ensuring the maximum uptime of machines. Basically, predictive maintenance uses time-based information and knowledge to report a possible failure avoiding downtime [22].

Predictive maintenance approaches are considered one of the crucial datadriven analytical applications for large-scale manufacturing industries and Industry 4.0 environments. Considering real cases in the area of predictive maintenance, it was identified that the requirements for a big data processing pipeline in the different phases of data processing such as data collection, analytics, querying, and storage [15]. Therefore, the data comes from different sources and formats. In this way, the data complexity in terms of its size, variety, and uncertainty is difficult to be analyzed using traditional techniques. Consequently, knowledge processing approaches including machine learning (ML), data mining, and deep learning techniques have extensively been used in many industry 4.0 applications (e.g., pattern recognition, product identification, product steering, predictive maintenance, scheduling, material flow control, and predictive analytics in supply chains) [18]. The use of ML algorithms is capable of fulfilling the task of prognostics and prediction of failures, for example, estimating the lifetime of a machine using a large amount of data to train a ML algorithm [16], in addition to being used to diagnose failures [1]. On the other hand, overcoming challenges include the need to integrate data from various sources and systems within a facility, which is important to gather accurate information to create prediction models [12]. In this sense, the predictive maintenance in Industry 4.0 and its applications, the several predictive maintenance uses cases, needs to utilize knowledge processing approaches for accurate failure predictions to enhance decision-making and maximize profit.

The ability to collect and analyze data to accurately predict failure patterns is crucial to a successful predictive maintenance strategy. However, engineers and scientists face challenges [8, 20] around process and data when applying predictive maintenance technologies into their business operations, such as, lacking data to create proper predictive maintenance systems, understanding failures but not being able to predict them, lacking failure data in order to improve the predictive models accuracy. Also, PdM can be expensive. A solid PdM setup requires a variety of different technologies to run efficiently. It may require significant investment to upgrade old equipment with smart assets or to integrate predictive technology into these aging machines [14].

3 InValue Experience

ISEP has acquired experience in the field of predictive maintenance through its involvement in the InValue project. The InValue project aims to develop a platform that, through an integrated set of technological solutions and processes, facilitates the adoption of good organizational practices and the implementation of predictive maintenance in the manufacturing industry.

The GECAD research center of ISEP and the companies SISTRADE, EVOLEO Technologies, FACORT and ISQ, collaborate in this project. Given the complexity of the problem, the development of the platform requires a multidisciplinary approach that involves concepts and technologies such as sensor technology, Big Data, intelligent data analysis and human-machine interfaces, among others.

The InValue platform was designed to facilitate the implementation of Predictive Maintenance approaches and is currently installed in a metallurgical company, specialized in custom precision parts production, which has begun its digitalization process. The platform is comprised of three layers (Fig. 1): (1) Data acquisition, (2) Data Processing and (3) Information delivery.

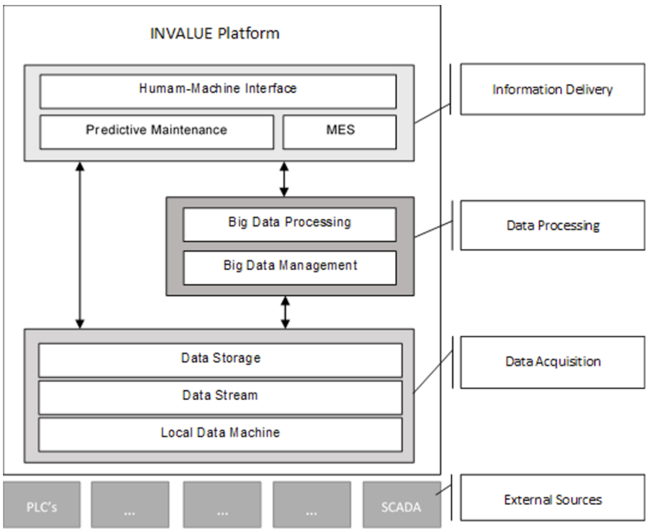

Fig. 1. InValue system's architecture [7].

The Data Acquisition module is capable of monitoring machines of different ages and technologies. The data generated by the machine (production data or provided by the machine's own sensors) are made available through a bus with the described protocol; Additional information of interest about the state of the machine that is not provided by the machines themselves is captured by a series of sensors previously installed for this purpose in mind. Moreover, relevant information can be provided by external systems, such as production management software, local SCADAs, etc. The Data Processing module is responsible for both data pre-processing and the use of ML and Data Mining techniques in order to identify components that may be approaching failure, diagnose failures and propose possible corrective measures. This information is delivered by the Information Delivery module not only to the end users concerned, but also to the Manufacturing Execution Systems (MES) in use.

InValue's Data Acquisition module captures large amounts of data at great speeds. The challenges that arise from the need to process this data can be tackled by the use of distributed architectures such as the Cloudera's distribution of Apache Hadoop. To satisfy the processing needs of the data extracted from InValue's relational warehouse, a small cluster (without high availability) comprised of four nodes, was set up. This particular set up is meant for development/testing purposes.

Considering the needs of SQL queries in a distributed environment for data analytics and the need to schedule diverse tasks, the following services were added: Hive, Hue, Yarn, Sqoop, Oozie, Zookeeper and Impala. Fig. 2, presents a simplified view of the distribution of roles and services through the nodes.

A small cluster without high availability must assign roles to three types of hosts: Master hosts, Utility/Edge hosts and Worker hosts. However, due to the very small size of the InValue cluster, composed of only four hosts, the responsibilities of the master host and the utility/Edge hosts are aggregated on Node 1, with the exception of the secondary NameNode, which is delegated to Node 4. As such, Node 1 is the NameNode and ResourceManager/JobHistoryServer, responsible for dividing data and assigning tasks through DataNodes/NodeManagers (Nodes 2 to 4). Work hosts include work responsibilities for Impala, Hive and Zookeeper. Regarding the InValue Big Data Analytics platform's, it is divided into two workflows: (a) batch processing for predictive model generation and (b) stream processing for real-time statistics and alerts. These two different scenarios are represented in Fig. 3.

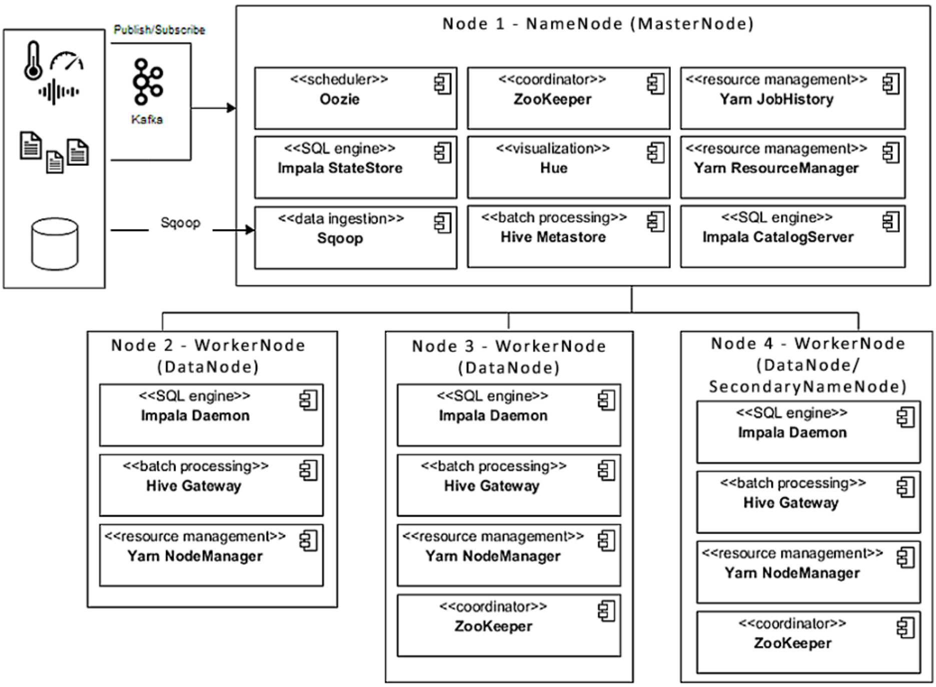

Fig. 2. InValue's Hadoop Cluster [6].

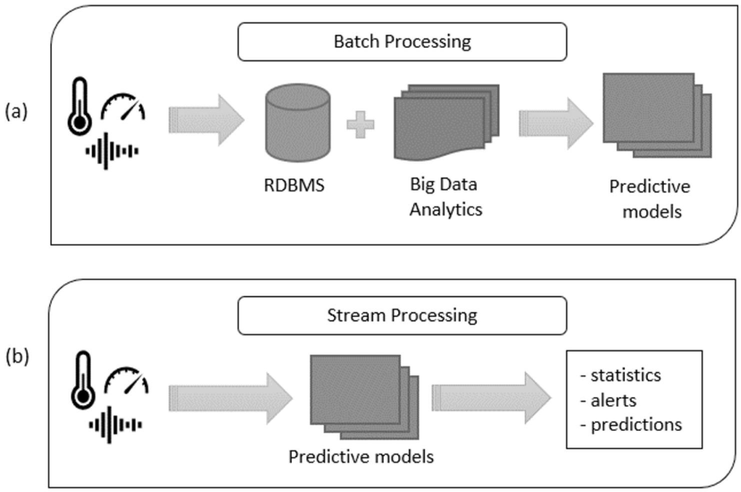

Fig. 3. InValue's Big Data Analytics platform workflows [6].

In an initial approach, data will be extracted from the relational database and processed in batch to generate a series of predictive models. These models will be used in a second future phase, where they will be executed in data flows to generate statistics, alerts and forecasts in real time.

4 Maintenance 4.0 Experience

The experience obtained by IPB, and particularly the CeDRI research center, in the topic of predictive maintenance is exemplified by the participation in the Maintenance 4.0 project, which is related to an intelligent and predictive maintenance system, aligned with an end-user interface for visualization and monitoring in a manufacturing enterprise. The Maintenance 4.0 project was oriented to the requirements of Catraport Lda company, located in Bragança, where the environment volatility is higher due to ts production system that produces components and accessories for the automobile industry using metallic stamping machines, which served as an experimental proof-of-concept of new applications in a real case.

A proper system architecture for condition-based maintenance was designed, comprising the cooperation of several modules, namely data acquisition and treatment, decision, communication and visualization, as illustrated in Fig. 4.

The ability to successfully integrating these modules is essential 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, ML and advanced data analysis [5].

Briefly, the data collection module is responsible for the automatic and manual collection of data, being able to retrieve data from several sources and store it in a database using IoT technologies. The database will feed the offline data analysis module, where the knowledge is generated through the use of advanced data analytics and ML techniques, e.g., rules to correlate different parameters to trigger the earlier identification of needs for maintenance interventions. The generated knowledge is used by the dynamic monitoring module that is responsible to apply the generated rules to the collected data, supporting the visualization of the machine health along the time but also the detection in advance of needs for maintenance interventions. Finally, the intelligent decision support module is responsible to provide a decision support guidance to the technician during the execution of maintenance interventions comprising human-machine interfaces (HMI) and augmented reality technologies.

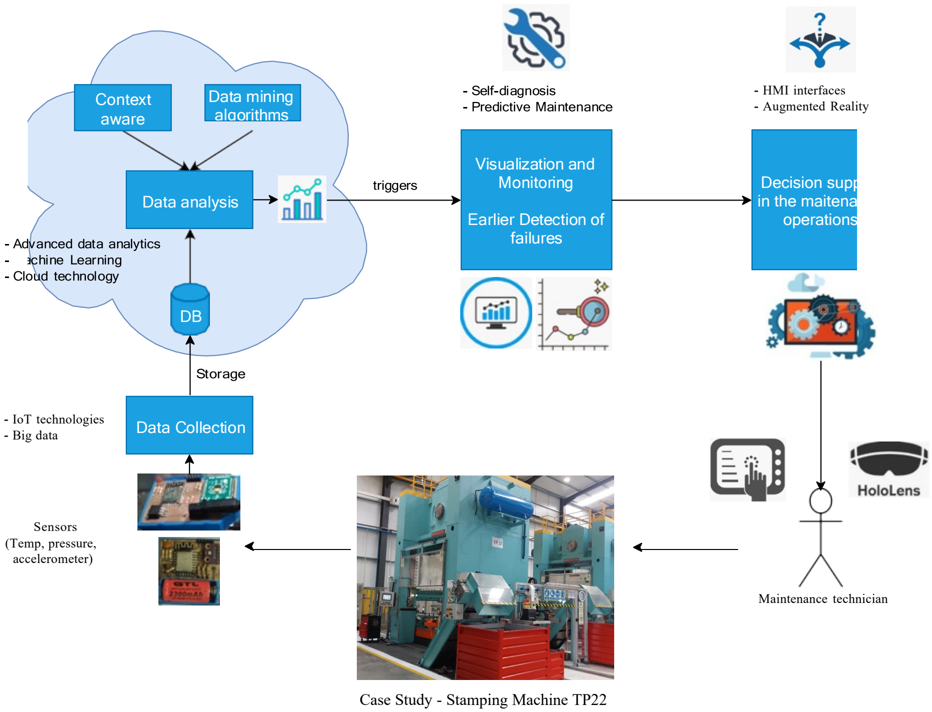

Fig. 4. Intelligent and predictive maintenance system architecture (adapted from [2]).

This basis of this experience considers the online analysis of the collected data where the production managers or supervisors could view and monitor the various parameters collected from the machine in real-time, as well as the statistical data relating to products, product failures or machine warnings reports. In addition, they can also monitor the probability of occurrence of some events, such as machine failures, according to models and forecasting algorithms that could help a timely decision-making. For this purpose, the data acquired and transmitted by all modules is visualized through a computational application developed according to a flow programming approach using the Node-RED platform [10].

Dashboards were developed, but one of them related regarding the display of data regarding failures or warnings, whether from product quality or machine health condition, providing monitoring and statistical information. In this way, the production manager uses this dashboard, (Fig. 5), to get a deeper insight of the current product quality (data regarding defects) or the machine operation health (machine failures).

Regarding the products quality, the dashboard displays for each type of defect, the total number of occurrences, the last occurrence of such defect (date), the time without defect (in days), the Mean Time Between Failure (MTBF) for a specific product defect, which is a crucial industry parameter to be taken into consideration, and is related to the average time between the occurrence of two consecutive failures.

Concerning an important research topic in this experiment, it was the development of an advanced data analysis module, for predicting events, failures or warnings, on the theme of predictive maintenance (bottom of the monitoring system presented in Fig. 5). This module takes 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 machine learning approach with supervised learning for the early fault prediction and predictive maintenance was developed, concerning the advantage of detecting underling patterns that may not be detected by a human operator/programmer [4]. 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.

Initially, the data analysis focused mainly on machine internal events, e.g., the log of machine errors, being proposed an evaluation of one machine learning approach, a type of recurrent neural networks (RNN), the long short-term memory (LSTM) network [13, 21, 3], that can correctly predict a fault in the next 5 minutes' block. After analysing the dataset regarding the machine failures (coming in.csv files), with more than 43.000 previous events, we started to integrate the early failure/warning prediction inference engine according to the collected files, which was codified in python. The Fig. 6 shows the overall model architecture that LSTM layer will feed with all sequences of events through each internal layer and the final LSTM state encodes the machine behaviour, including relations between past and recent events, in this case as a supervised problem up to 5 previous samples.

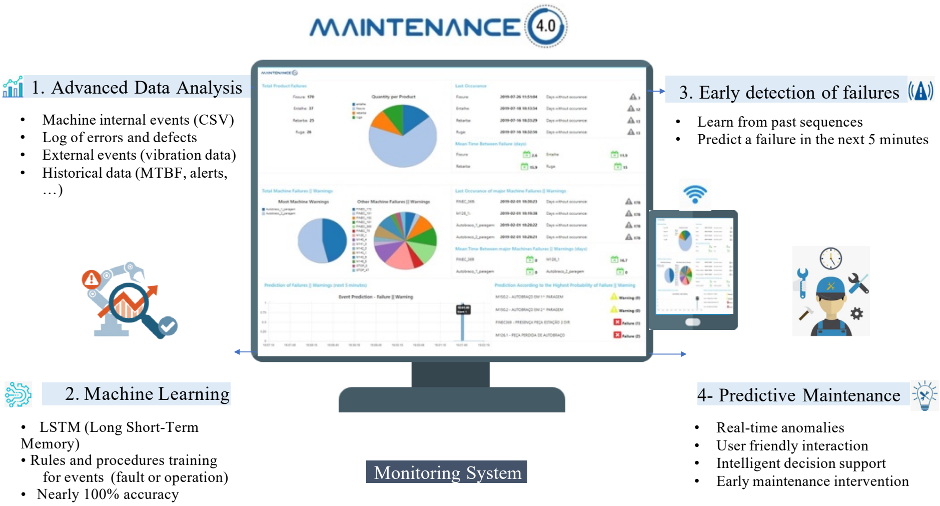

Fig. 5. Dashboard for the visualization and monitoring of the statistical data related to product's defects, machine's failures and early fault prediction.

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, 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 fails, i.e. almost 98% of the original machine events are warnings, resulting in an 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) [2].

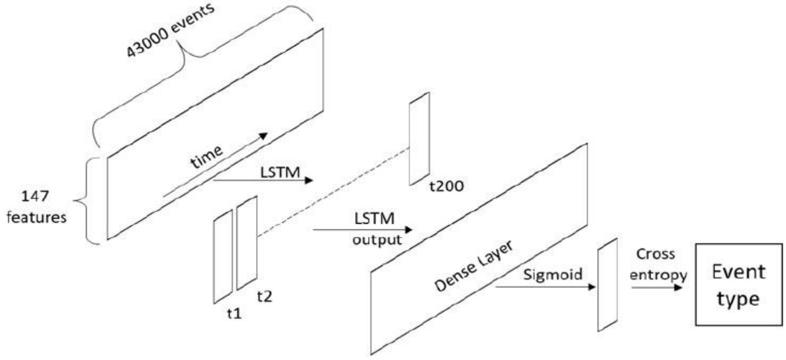

Fig. 6. Proposed RNN model architecture based on a LSTM layer to predict the next failure/event type [5].

Fig. 7 represents the results for the training and validation accuracy and loss for the 150 neuron configuration and considering the range up to 30 epochs.

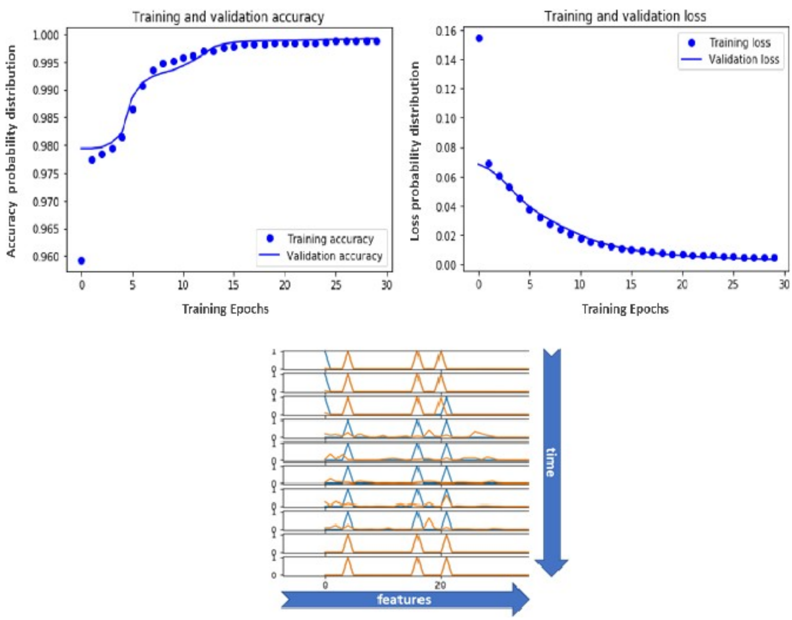

Fig. 7. Top Training and validation accuracy and loss for 150 neurons; Bottom Sample of prediction vector (orange line), with probability of anomaly at index 0 of feature axis, the following index are the type of event.

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. At the bottom of the Fig. 7, the orange line represents probability of an event and the blue line the ground-truth. The left most feature (index 0) is the overall fault probability and the following are types of events (including from faults types to normal operational events).

The output is interpreted, communicated and represented in real-time through the graph shown at the bottom of the monitoring system (Node-RED dashboard) in the bottom of the monitoring system, from Fig. 5. The probability of fault is being predicted for the next 5 minutes, in a graph, when vertical lines with the value 1 on the y-axis appear, it represents the type of failure that can occur, which is accessed in dynamic way to the type and name of the failure to be predicted. In overall, the proposed algorithm was able to predict and detect anomalies from internal and external data sources, showing that is possible to improve the device/system availability by performing earlier the maintenance interventions.

In addition to the dashboard application for visualization and monitoring, an Android mobile application was developed, to support the remote monitoring, and provide to the user the ability to check the machines' status, that, either by WiFi or VPN and will have the ability to access via the dashboard's IP.

5 Conclusions

This work presents two intelligence maintenance solutions integrating artificial intelligence algorithms for prediction to support the industrial maintenance, further minimizing the effects and impact of unexpected failures in the production system, and consequently increasing the competitiveness of manufacturing enterprises, provided and researched by two Higher Institutes in Portugal, IPB in Bragança and ISEP in Porto.

Within the scope of the INVALUE project, wich ISEP was involved, a predictive maintenance platform was developed capable of supporting the companies decision making, collecting data from industrial machines and using ML techniques to extract useful knowledge from them. A pilot version of the platform was tested at the end user's facilities, whose predictive system uses predictive models to analyze the monitoring data of the machines in real time and detect the occurrence of early failures. The predictive system is complemented by a system of rules whose purpose is to assist in the detection of failures and provide information that can be used by the management team to optimize production. The use of the INVALUE platform in a real environment has demonstrated its ability to improve the company's operations and thus increase its competitiveness.

In relation to IPB, the proposed system architecture considers the advanced and online analysis of the collected data for the earlier detection of the occurrence of possible machine failures, dynamic monitoring and supports technicians during the maintenance interventions by providing a guided intelligent decision support. Additionally, the collected data is analysed by a ML algorithm that allows to predicts earlier the problems, and generate warnings for the implementation of maintenance interventions that will mitigate their occurrence.

Although, several limitations still exist either due to data availability, the process digitalization or technician learning curve, this work enabled the development and validation of the several architectural modules in practice, i.e. in a real industrial production unit for metal stamping for the automotive sector. The partnership with an automotive industry and application in real context, showed that the experience developed in the Maintenance 4.0 project leveraged an importance of maintenance management that 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.

The Industry 4.0 will continue to evolve and certainly more contributions and experiences in predictive maintenance will be applied continuously to support manufacturing systems or other interventions. The experience gained in these reports will provide the knowledge and expertise for more projects in the future.

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