A RAMI 4.0 View of Predictive Maintenance: Software Architecture, Platform and Case Study in Steel Industry

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Abstract. The fourth industrial revolution is characterized by the introduction of the Internet of Things (IoT) into manufacturing, which enables smart factories with vertically and horizontally integrated production systems. The key issue of any design and system development in the context of Industry 4.0 is the proper implementation of Reference Architectural Model Industrie (RAMI) 4.0 in various manufacturing operations and the definition of appropriate sub-models for individual aspects and processes according to the technical background of Industry 4.0. Since maintenance is increasingly considered a strategic business function which contributes to overall reliability and profitability, predictive maintenance, as a novel lever of maintenance management, has been evolved. Predictive maintenance is a significant enabler towards Industry 4.0. In this paper, we design a predictive maintenance architecture according to RAMI 4.0. On this basis, we develop a unified predictive maintenance platform and we apply it to a real manufacturing scenario from the steel industry.

Keywords: Industry 4.0 · Predictive maintenance · Industrial Internet of Things · Steel industry

1 Introduction

The fourth industrial revolution is characterized by the introduction of the Internet of Things (IoT) into manufacturing, which enables smart factories with vertically and horizontally integrated production systems [1]. The physical and virtual worlds grow together and objects including machines are equipped with sensors and actuators [1]. The key issue of any design and system development in the context of Industry 4.0 is

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the proper implementation of Reference Architectural Model Industrie (RAMI) 4.0 in various manufacturing operations and the definition of appropriate sub-models for individual aspects and processes according to the technical background of Industry 4.0 [2, 3]. To do this, several aspects should be taken into consideration, such as interoperability of devices and software components, cloud computing technologies, big data analytics and artificial intelligence [4].

Predictive maintenance has gathered a lot of attention by manufacturing firms and thus, several industrial and research works have focused on its implementation with sensory technologies, software systems and appropriate systematic methodologies. However, the scarcity of pilot cases in predictive maintenance, capable of proving its benefits, has led to the lack of implementation of predictive maintenance initiatives extensively in industry [5]. The systematic representation of a predictive maintenance solution enables the reusability and knowledge transfer, an aspect of outmost importance in Industry 4.0 platforms [6]. In this paper, we examine how RAMI 4.0 can be applied in the design of a software architecture for predictive maintenance. Moreover, we illustrate how the architecture can be used to develop a platform which covers all the aspects of predictive maintenance. The predictive maintenance platform is applied to a case from steel industry.

The rest of the paper is organized as follows: Sect. 2 presents a literature review about Industry 4.0 and predictive maintenance. Section 3 describes a predictive maintenance architecture as an instantiation of RAMI 4.0, while Sect. 4 presents its implementation to a platform. Section 5 describes an application of the predictive maintenance platform in a case from the steel industry. Section 6 concludes the paper and presents our plans for future work.

2 Literature Review

2.1 Industry 4.0

Industry 4.0 is defined as "the flexibility that exists in value-creating networks is increased by the application of Cyber Physical Systems (CPS). This enables machines and plants to adapt their behavior to changing orders and operating conditions through self-optimization and reconfiguration" [7]. Moreover, perceiving information and extracting business insights from the huge amounts of heterogeneous data is a key technological challenge in Industry 4.0 [6, 8, 9]. Industry 4.0 brings changes in the architecture of the classical control pyramid of production complexes as well as technological processes. The RAMI 4.0 is a three-dimensional model representing different interconnected features of the technical – economical properties and showing how to approach the issue of Industry 4.0 in a structured manner. It consists of three axes: (i) the hierarchy levels; (ii) the architecture layers; and, (iii) the lifecycle value stream.

Hierarchy Levels. The Industry 4.0 architecture at hierarchical level shows a functional assignment of components [3]. This axis within an enterprise or factory follows the IEC 62264 and IEC 61512 standards. The level over and below the IEC standards area represents steps further and describes also groups of factories, collaboration within external engineering firms, component suppliers and customers. Therefore, the hierarchy levels are: product, field device, control device, station, work center, enterprise, and connected world.

Architecture Layers. The architecture layers include the following: Asset Layer, Integration Layer, Communication Layer, Information Layer, Functional Layer, Business Layer. They enable the development of Industry 4.0 software solutions in a consistent way so that different and mutually dependent manufacturing operations are interconnected taking into account the physical and the digital world.

Lifecycle Value Stream. The lifecycle value stream axis is divided to Type and Instance. The Type is divided to Development and Maintenance/Usage, while the Instance is divided to Production and Maintenance/Usage [7]. A type represents the initial idea, while each manufactured product represents an instance of that type [7]. The value stream in the totally digitized production can be viewed in conjunction with value-adding processes, since it enables linking of purchasing, production planning, logistics, quality, customers and suppliers [7].

2.2 Predictive Maintenance

Manufacturing companies are increasingly considering turning to predictive maintenance by utilizing the capabilities of condition monitoring. The emergence of the Internet of Things (IoT) paves the way for enhancing the monitoring capabilities of enterprises by means of extensive use of physical and virtual sensors enabling them to decide and act ahead of time [10], i.e., to resolve problems before they appear (e.g. to avoid or mitigate the impact of a future failure). To this end, predictive maintenance has been evolved as a novel lever of maintenance management. However, predictive maintenance and associated information systems have received several criticisms due to their complexity and to their challenges for practical implementation [5], since they handle massive information, changing on time, and with complex relationships among them. For example, structuring the information sustainably and interrelating properly the consisting software services is a significant challenge in the complex and dynamic manufacturing environment [5, 11].

Several conceptual frameworks for predictive maintenance have been proposed in the literature [5, 11–15]. The most recent approach proposes a unified predictive maintenance framework covering the whole information processing lifecycle [15]: Signal Processing, Feature Extraction, Diagnosis, Prognosis, Decision Making & Actions Planning. These (near) real-time steps are fed by the Failure Mode, Effects and Criticality Analysis (FMECA) model and Historical Data Analytics, while the user interaction is facilitated with configuration and visualization capabilities.

3 A RAMI 4.0 View of Predictive Maintenance

The motivation for using RAMI 4.0 to scope and design a predictive maintenance architecture is the need to frame developed concepts and technologies in a common model that leverages further collaboration and integration with other industrial architectures and systems in the frame of Industry 4.0. This is a challenging task since the Industry 4.0 paradigm is still evolving with limited past experience of successful implementations. Our approach focuses on instantiating RAMI 4.0 to maintenance operations and examining how a unified predictive maintenance platform can be developed based on RAMI 4.0 – compliant architecture. Designing a unified predictive maintenance conceptual architecture in the context of RAMI 4.0 enables the integration of the maintenance process with the other operations and processes of the manufacturing enterprise based upon the Industry 4.0 paradigm. The following sub-sections describe the three axes of RAMI 4.0 in the context of predictive maintenance.

3.1 Hierarchy Levels

The predictive maintenance architecture in the frame of RAMI 4.0 is applicable at component, machine or production process level. In this sense, it can be implemented in flexible smart systems and machines capable of interacting and communicating across the hierarchy levels through a network. The implementation of the architecture in a "Connected World" (i.e. connected factories with integrated predictive maintenance processes) would require its use by all of them in order to create synergies (e.g. between a factory and its supplier of maintenance spare parts).

3.2 Architecture Layers

Figure 1 shows the predictive maintenance architecture in the frame of the RAMI 4.0 architecture layers. The individual layers and their interrelationships are described below.

Asset Layer: Since this layer represents the reality ("physical things in the real world"), production equipment and users are part of it. Predictive maintenance is implemented on the *Production Equipment* with the involvement of the platform *Users*. The production equipment can be further analyzed to "System", "Equipment Unit" and "Maintainable Item" according to the Industry Standard Solution for Plant Maintenance (ISPM)[1], which is based upon and extends the ISO 15926-2 [16] and the ISO 14224:2006 taxonomy [17].

Integration Layer: This layer makes provision of information on the assets in a form which is available for computer processing by connecting elements as well as people with IT. The integration of the information sources is critical for ensuring the reliability of the information and controlling the performance of the monitoring system [18]. This layer involves the equipment-installed *Sensors* and the *Legacy Systems* (MES, ERP, etc.). It also includes the *Human Machine Interfaces* of the legacy data systems (e.g. ERP GUI) and of the predictive maintenance platform (GUI for configuration) through which the users insert data.

Communication Layer: Since this layer provides standardization of communication by means of uniform data format and deals with the physical support of information processing (mainly according to the ISO 13374 standard [19] as implemented by

[1] https://reliabilitydynamics.com/Industry-Standard-Solution-for-Plant-Maintenance.

MIMOSA OSA-CBM [20]), it includes the *IoT Gateway*, the *Legacy Data Uplifting* and the *Event Broker*. In this way, a predictive maintenance platform gathers the data from the information sources for further processing in the subsequent Information Layer.

Information Layer: This layer provides pre-processing of events and execution of event-related rules by enabling their formal description for the interpretation of the information. It also manages data persistence, ensures consistent data integrity and transformation for feeding into the Functional Layer. Therefore, it includes sensor and legacy data pre-processing while feeding into the *Stream Processing* and the *Batch Processing* environment respectively. To this end, this layer also includes the *predictive maintenance platform's DB* and the *Time-Series DB* for the real-time sensor measurements. In this way, the required data are extracted and combined accordingly in order to be available by the functions of the next layer. This process is also in accordance to Data Acquisition and Data Manipulation of the ISO 13374 standard as implemented by MIMOSA OSA-CBM.

Functional Layer: This layer enables the formal description of functions and creates the platform for horizontal integration of various functions. It contains the run time and modelling environment for services supporting the business processes and a run time environment for applications and technical functionalities. In this layer, the following functions, which are executed on the basis of data integrity of the previous layer, take place:

- *System Definition*: The definition of all aspects regarding the manufacturing system including failure causes, failure modes and effects along with appropriate reactive and proactive actions, as well as the specification of the failure concepts and instances that affect the monitored systems. It is derived from FMECA.
- *Risk Assessment*: The criticality of the manufacturing system's assets and the indication of the most critical ones. The outcome is a risk matrix which highlights the most critical parts of the system. This is also derived from FMECA.
- *Batch Data Analytics*: Advanced data analytics algorithms based on legacy and operational data related to the maintenance activity. It generates offline models and rules that are used by Stream Data Analytics and Decision Making functions.
- *Stream Data Analytics*: Descriptive and predictive analytics on the basis of data streams generated by sensors. Descriptive analytics includes algorithms for real-time anomaly detection (diagnosis), while predictive analytics includes algorithms for real-time failure predictions (prognosis) for various failure modes according to the system definition. These functionalities are in accordance with ISO 13374 as implemented by MIMOSA OSA-CBM (in the sense that diagnosis refers to State Detection and Health Assessment, while prognosis refers to Prognostics Assessment) as well as with ISO 13379 [21], ISO 17359 [22] and EN 13306 [23].
- *Decision Making*: Prescriptive analytics on the basis of real-time failure predictions. It includes algorithms for proactive decision making (e.g. about the optimal actions and their optimal times) and the formulation of the maintenance plan including both preventive and proactive actions, upon user approval. This functionality is in accordance with ISO 13374, as implemented by MIMOSA OSA-CBM in the sense that it refers to Advisory Generation, as well as with EN 17007 [24].

Business Layer: This layer ensures the integrity of functions in the value stream and enables mapping business models and the outcomes of the overall process. It takes into account the policies, rules and constraints according to which the system operates through the interrelationships of predictive maintenance to other manufacturing operations. It also creates a link among different business processes, i.e. other interrelated *Manufacturing Operations* (e.g. logistics management, quality management, production planning), through the exposure of appropriate information to the user. In this sense, this layer involves the *User Interaction* with the predictive maintenance platform (e.g. configuration, feedback, etc.), the *Real-time Monitoring* and the *Visualization* functionalities.

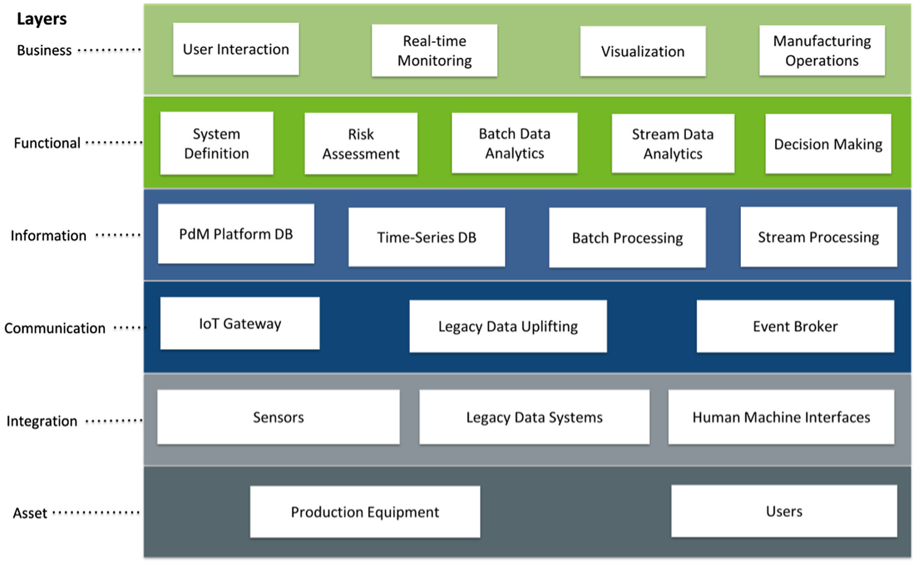

Fig. 1. Predictive maintenance architecture in the context of the RAMI 4.0 architecture layers.

3.3 Lifecycle Value Stream

The lifecycle value stream of predictive maintenance has both managerial and technical implications. As far as the managerial perspective is concerned, the type includes the idea as well as the development and validation of a predictive maintenance strategy. After successful validation, the new consulting service is released. Each instantiation of the predictive maintenance strategy to a specific production process or industry represents an instance of that type. As far as the technical perspective is concerned, the type includes the idea as well as the development and testing of a unified information system for predictive maintenance which sets the basis for serial production. Each instantiation of the predictive maintenance information system to a specific equipment, production process or industry, and to a specific legacy data system or installed sensor represents an instance of that type.

4 The UPTIME Software Architecture and Platform

The predictive maintenance architecture in the frame of RAMI 4.0 was implemented as an e-maintenance platform in the context of the EU H2020 Unified PredicTIve MaintenancE (UPTIME) project. Figure 2 depicts the technical architecture of the UPTIME e-maintenance platform (in accordance with RAMI 4.0) which shows the main interactions among the components through the definition of end-to-end integration and communication processes. The technical architecture consists of three tiers: Presentation Tier, Logic Tier, and Data Tier.

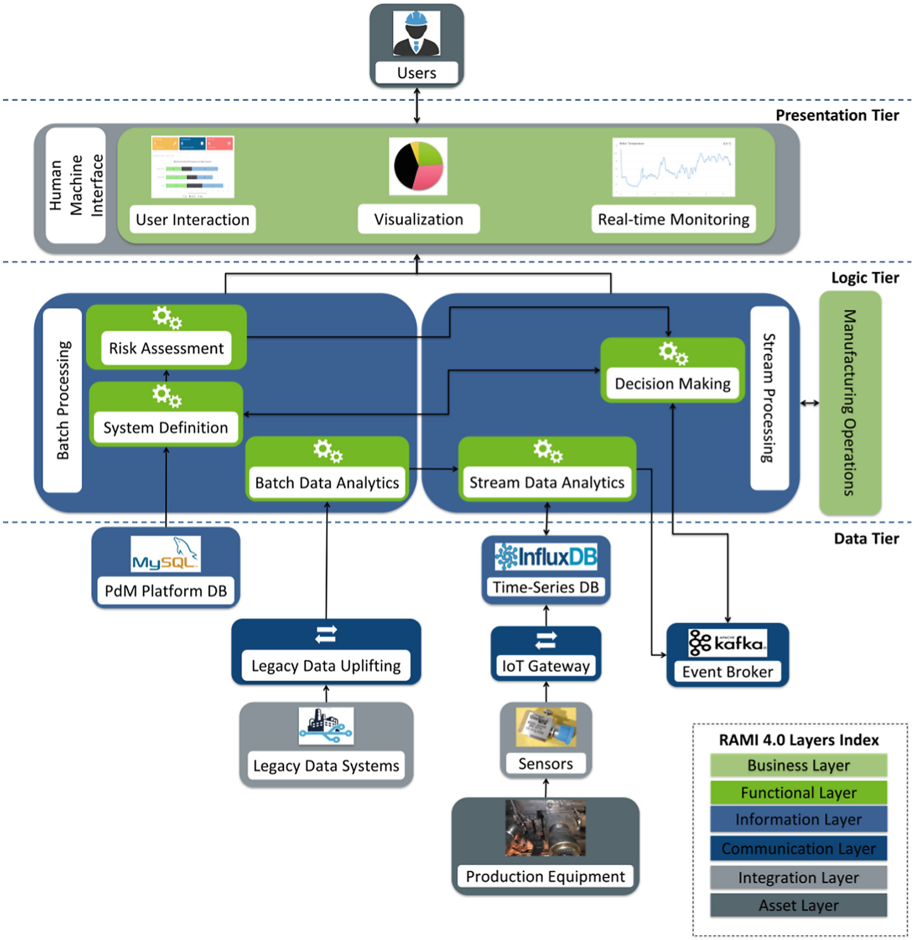

Fig. 2. The technical architecture of the UPTIME e-maintenance platform.

Presentation Tier: The Presentation Tier is implemented through a Graphical User Interface (GUI) which includes a menu consisting of the following items: Overview, Stream Data Analytics, Batch Data Analytics, Decision Making, Risk Assessment, System Definition. The main screen is shown in Fig. 3. Each one of these items is used for configuration, real-time monitoring and visualization of the results. Figure 3 provides an indicative depiction of the Overview screen of the UPTIME GUI. It includes aggregated information, easily accessible by the user, by incorporating advanced visualization capabilities with the use of Elasticsearch[2].

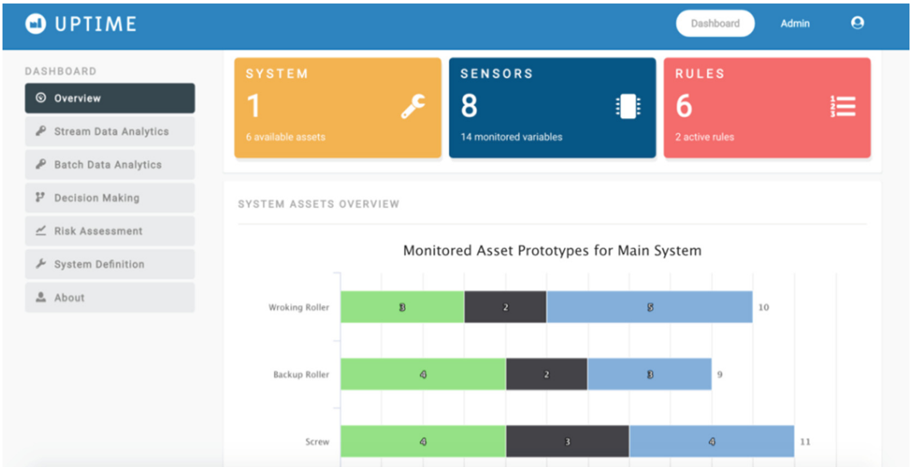

Fig. 3. The Overview screen of the UPTIME platform.

Logic Tier: The Logic Tier is implemented by integrating the core functionalities for predictive maintenance in Industry 4.0 (i.e. from the Functional Layer of RAMI 4.0). The System Definition and the Risk Assessment is initialized based on expert's input, while the Batch Data Analytics is fed by the legacy data. The sensor data are interlinked with those persisted in the UPTIME database in order to ensure the proper mapping among the sensor data and the instances that derived from the system definition. Kafka[3] orchestrates the whole end-to-end integration process. For the Stream Data Analytics and Decision Making functionalities, Kafka is the actual message broker where components can subscribe to, in order to consume data that are produced asynchronously and delegated among the various components.

Data Tier: The Data Tier of the UPTIME platform consists of two main parts: On the one hand, the UPTIME solution provides data harmonization in terms of manipulating streaming data from sensors. On this basis, the InfluxDB time-series database has been installed. On the other hand, the common UPTIME database, which is represented by a

[2] https://www.elastic.co/.

[3] https://kafka.apache.org/.

MySQL database handling the operations of the UPTIME platform, ensures consistency during the lifecycle of the platform. The UPTIME platform uses also the data that are stored in the legacy systems.

5 Application in the Steel Industry: The M. J. Maillis S.A. Case

The steel sector has been getting pressure from all sides in recent years as raw materials have become more expensive or difficult to source and growth has slowed to a crawl. The steel industry is strategic in the EU economy. With an average production of 170 million tons of steel per year at more than 500 steel production sites across 24 EU member states and with its close integration to Europe's manufacturing and construction industries, the steel sector is crucial for development, growth and employment in Europe [25]. Steel-making is a complex industrial process and defects introduced in early stages have an economic impact in posterior transformation.

The case under examination is the cold rolling process of M. J. Maillis S.A. Cold rolling is a process of reduction of the cross-sectional area or shaping a metal piece through the deformation caused by a pair of rotating in opposite directions metal rolls. Cold rolling occurs with the metal below its recrystallization temperature. In cold rolling mill production lines, M. J. Maillis S.A. uses cold rolling mills to produce rolling products with the closest possible thickness tolerances and an excellent surface finish. Given an entry steel coil of 4 tons weight and thickness of 2 mm, it produces steel strips over the whole thickness spectrum until 0.4 mm. The most important components of the milling station are summarized below:

- **The work rollers.** This pair of rollers is responsible for the actual milling; the material is passed through the gap between them and in a sequence of passes is milled to the desired width.
- **The backup rollers.** This pair of rollers (one backup roller for each working roller) transmits motion to the working roller.
- **The motor unit**, which is responsible for rotating the backup rollers.

Figure 4a depicts the milling station; Fig. 4b represents the manufacturing process of the milling station; while Fig. 4c shows the work and the backup rollers and sensors' positions. During the operation, the whole contents are enclosed and all the rollers are continuously being sprayed by soap oil in order to reduce heat and friction.

The main sensor infrastructure setup, which is used for data acquisition, is depicted in Fig. 5. All sensors are collected in an MVX which are then transmitted via Modbus TCP to a Siemens S7-1500 PLC. The values are exposed from the PLC to the DB port and can thus be collected external modules that have access to the PLC via network. An adapter samples the DB Port every 5 ms–5 s. The sampling rate can be configured and they generally depend on the variable. The data are then processed via a Storm-Kafka pipeline. This pipeline is responsible for performing normalization procedures. Normalization is also configurable and can be adjusted by attaching new Storm Bolts. 10 Accelerometers collect data relevant to vibrations, while one tachometer measures the speed of the motor and one current sensor measures the current of the motor. Accelerometers measure a set of four variables for vibration-related data (overall acceleration, overall velocity, sock finder and overall bearing defect), tachometer measures in rpm units, while the current sensor measures in Ampere.

The UPTIME platform is connected to the sensor infrastructure so that the generated data along with the data collected from the legacy and operational systems are processed accordingly. Below, we describe an illustrative predictive maintenance scenario covered by the UPTIME platform for the M. J. Maillis S.A. milling station.

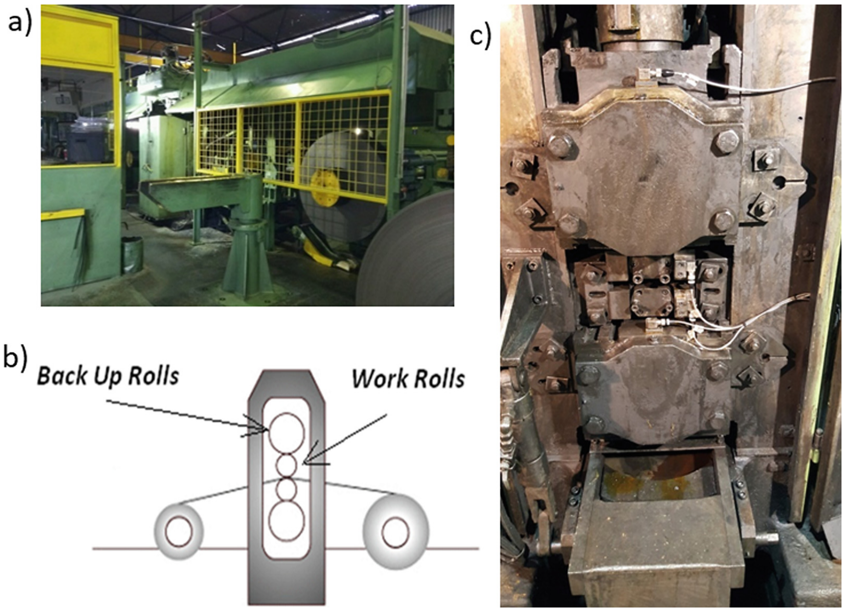

Fig. 4. The M. J. Maillis S.A. milling station: (a) an overview; (b) a representation of the manufacturing process; (c) the rollers when the main casing is open.

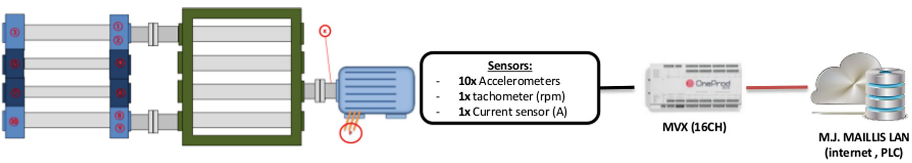

Fig. 5. Infrastructure setup for sensor data collection.

At design time, the user configures the platform through the *System Definition* and the initial *Risk Assessment* according to the assets, the failure causes, the failure modes and effects, i.e. taking into account the FMECA modelling of the manufacturing system. Other parameters, such as the costs of failure modes, the costs of maintenance actions, the failure thresholds, etc., are retrieved from legacy data uplifting and are updated dynamically, on a batch mode, as soon as new data is added. The latter is executed through *Batch Data Analytics* which implements machine learning and data mining algorithms such as Self-Organizing Maps (SOMs), k-means clustering, decision trees and association rule mining.

At runtime, the UPTIME platform provides real-time monitoring of the measured parameters (e.g. vibration) and ensures that the gathered data at the on-site PLC are transmitted through the communication channel. The acquired data feed into the *Stream Data Analytics* functionalities which subsequently perform feature extraction and anomalies detection (diagnosis), with algorithms such as Long Short-Term Memory (LSTM), as well as failure predictions (prognosis) (e.g. Remaining Useful Life, time-to-failure or failure Probability Density Function), with algorithms such as curve fitting, neural networks and Hidden Markov Models (HMM). The prediction about the roll break feeds into the *Decision Making* functionality which recommends the optimal proactive actions (e.g. lower the speed, increase the soap oil flow or perform full maintenance) along with their optimal times. To do this, it implements decision methods such as Markov Decision Process (MDP). Upon user approval through the GUI, the recommended actions are inserted in the maintenance plan. The models used in Stream Data Analytics and Decision Making functionalities are updated on the basis of the Batch Data Analytics outcomes as soon as new data is collected.

6 Conclusions and Future Work

A key issue of any design and system development in the context of Industry 4.0 is the proper implementation of RAMI 4.0 and the definition of appropriate sub-models for individual manufacturing operations [2, 3]. Predictive maintenance is a significant enabler towards Industry 4.0. However, up to now, it has not been considered in the frame of RAMI 4.0 in order to result in a unified predictive maintenance platform. In this paper, we designed a predictive maintenance software architecture according to RAMI 4.0. On this basis, we developed the UPTIME platform and we applied it to a real manufacturing scenario from the steel industry. Regarding future work, we aim to further develop advanced algorithms for all the aforementioned steps of predictive maintenance. Moreover, we will evaluate the results in three manufacturing scenarios from the steel industry, the home appliances industry and the aviation industry.

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