Predictive Maintenance in Industry 4.0

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ABSTRACT

In the context of Industry 4.0, the manufacturing related processes have shifted from conventional processes within one organization to collaborative processes cross different organizations, for example, product design processes, manufacturing processes, and maintenance processes across different factories and enterprises. The development and application of Internet of things, i.e. smart devices and sensors increases availability and collection of diverse data. With new technologies, such as advanced data analytics and cloud computing provide new opportunities for flexible collaborations as well as effective optimizing manufacturing related processes, e.g. predictive maintenance. Predictive maintenance provides a detailed examination of the detection, location and diagnosis of faults in related machineries using various analyses. RAMI4.0 is a framework for thinking about the various efforts that constitute Industry 4.0. It spans the entire product life cycle & value stream axis, hierarchical structure axis and functional classification axis. The Industrial Data Space (now International Data Space) is a virtual data space using standards and common governance models to facilitate the secure exchange and easy linkage of data in business ecosystems. It thereby provides a basis for creating and using smart services and innovative business processes, while at the same time ensuring digital sovereignty of data owners. This paper looks at how to support predictive maintenance in the context of Industry 4.0? Especially, applying RAMI4.0 architecture supports the predictive maintenance using FIWARE framework, which leads to deal with data exchanging among different organizations with different security requirements as well as modularizing of related functions.

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CCS CONCEPTS

• CCS → Computer systems organization → Distributed architectures • Software and its engineering → Designing software

KEYWORDS

Collaborative business process, Industry 4.0, FIWARE, Industrial data space, Blockchain, Predictive maintenance analytics

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1 Introduction

Being widely adopted by industry, the focus of BPM, "a systematic and structured approach to analyze, improve, control, and manage business processes" face new challenges and opportunities. Process models focusing only on the control flow become insufficient. The dynamic nature of market demands, competitions and globalization, short life cycle of product force organizations to work beyond its boundary including machines/devices collaboration [1, 2, 3]. This demands enterprises with different business interests and competitiveness to work together for a defined business goal [3].

Collaboration enables multiple partners to produce a common business goal by integrating their agreed business process [3]. Traditional manufacturing like physical machines, devices, etc. are slow, long process, expensive as well as inefficient in dealing with the challenges created by short product lifecycle, dynamic nature of market demands, competitions and globalization [1]. Collaborative business processes are required being moved across factories and enterprises to effectively manage and ease the life cycle of production and its demands [1, 4]. For instance, virtual factory, a major expansion upon virtual enterprises in the context of manufacturing, enable the creation of new business ecosystems by integrating the collaborative business processes from different enterprises to simulate, model and test different design options, to evaluate performance, saving time-to-production [4].

Modular collaboration, the capability of enabling plugin or re-configure processes, devices, machines without a need for extensive re-development/engineering effort, is essential to enabling the flexibility (plugin/out) for cross-organizations to work seamlessly [1]. This means that organizations can connect devices with required data to perform business functions, enabling the maximum capacity of establishing instant collaboration among collaborative partners [1]. However, collaborative business process requires maintaining trust and transparency among partners [5]. Traditional collaborative business processes typically operate by exchanging messages between different partners via web services or sharing a collaborative database [6, 7]. These collaborations are often based on the centralized approach, which requires an authorized agent and subsequently poses challenges such as trust and traceability [5].

Blockchain as data storage has the potential to provide trust and traceability of business process data for the collaborative environment. Several attempts have made in the research community to provide solutions for collaborative business process based on blockchain technology [5, 9, 30, 31, 34]. However, blockchain technology platform still poses several key challenges including scalability, performance, security and business use cases [5, 8, 9]. One important approach to tackling these challenges is to take advantage of blockchain as data asset approach, rather than running collaborative business processes entirely.

The emerging Industry 4.0 drives the focus of modern industrial collaborative computing [10]. 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 behaviours to changing orders and operating conditions through self-optimization and reconfiguration" [11]. Essentially the data exchanged and produced in such interaction among several components establishes the underlying business processes for collaboration.

With the demand for data to flow across different collaborative domains, new important challenge like data sharing, transparency and traceability arise. Besides, the huge amount of data heterogeneous generated and collected from the many connected devices such as sensors, processes and systems pose challenges and opportunities such as data driven discoveries such as analytics [12, 13, 14]. The continuous growth of big data and its usage can provide new opportunities to operations and maintenance process to be proactive with ongoing equipment maintenance and upkeep [12, 13, 15]. This enables to predict upcoming potential issues in a system or equipment and, therefore utilize maintenance in a predictive manner, rather than relying on the costly approaches such as manual and random maintenance. However, the huge volumes of data become impossible for the traditional data processing and tools for analytics with a flexible and modular platform in the context of Industry 4.0 [1, 10, 14, 16].

This paper looks at how to support predictive maintenance in the context of Industry 4.0 by applying RAMI4.0 architecture supports the predictive maintenance using FIWARE framework, which leads to deal with data exchanging among different organizations with different security requirements as well as modularizing of related functions. The contributions of this work are: a) to design a predictive maintenance analytics platform based on RAMI 4.0 and FIWARE, b) to investigate and introduce a collaborative data exchange method based on IDS and Blockchain, and c) using the design predictive maintenance platform to present the application case.

The structure of the paper is as follows: Application case for predictive maintenance and background are provided in Section 2 and 3. IDS and blockchain for predictive maintenance, and the proposed design solution are presented in Section 4 and 5. A short discussion is presented in section 6, and the future work and conclusion are provided in Section 7.

2 Application case for predictive maintenance

The performance and condition of the production equipments are critical to the whole manufacturing process. Any unplanned failure or inefficient process of a component of manufacturing equipment can have a negative economic impact for an entire production line, resulting unplanned downtime and costs [17, 18]. Traditional maintenance approaches such as manual maintenance is inefficient and cumbersome in collecting equipment data due to the general concern of trust, discrete support and limited data available from competitive equipment manufacturers. Internet of technology like RFID/sensor technology enables to collect data but the process is complex, and the huge volumes of data is impossible for the traditional data processing and tools for producing meaningful information [16].

The continuous collection of huge data and its usage from the equipment can provide new opportunities to operations and maintenance process to be proactive with ongoing equipment maintenance and upkeep [17, 18]. This enables to optimize the operation and condition of the equipment as well as predict future potential issues in a system or equipment and, therefore utilize maintenance in a predictive manner. In order to achieve an optimal maintenance decision making, new approach should be in place to integrate multiple data sources from different data domains. Typically, production data, machine functional and operational data, and sensor data are all required for analysis (real-time, off-line) and used to build models for predicting machine failure or inefficient process or poor product quality reducing failure times and costs.

A flexible manufacturing factory consists of a processing system, a logistics system, an information system, and an auxiliary system. A concrete scene of the flexible factory is shown in Figure 1. The processing system in the scene consists of 4 sets of equipment, which consists of a three-dimensional warehouse, numbers of AGV trolleys, three robots, a carrier board and a carrier plate. Coordinate measuring machine (CMM) is responsible for the measurement. A cleaning machine and a drying machine are responsible for cleaning and drying the workpiece.

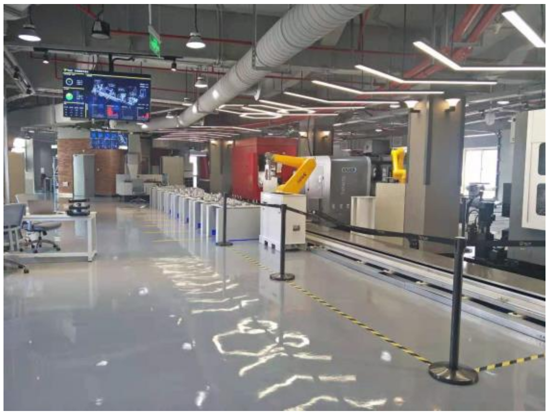

Figure 1: Flexible Manufacturing Factory

The workpiece is put on a universal tray with high re-positioning accuracy, which allows the different workpieces can be easily and quickly positioned and clamped. The RFID chip with the identification of each workpiece is fixed on the tray. After all workpieces are loaded on a carrier board, the carrier board is transported from the preparation area into the rough machining area by an AGV.

Depending on the processing requirements of each workpiece, the robot moves a workpiece to the roughing equipment for roughing machining, after roughing, the robot moves the workpiece for cleaning and drying equipment for cleaning and drying, and then the workpiece is transported by the robot to the area to wait for fine machining. The fine machining is similar to roughing machining. The robot moves the roughing finishing workpiece into the machine, and after processing, it is transported for cleaning and drying.

At the quality control stage, the finished workpiece is carried by the robot to the three-coordinate measuring machine. After the test is completed, the workpiece is moved to the area to further processes. If the result of the quality control is not satisfied, the workpiece may need to be redone. If the result of the quality control is fine, the workpiece is moved to a warehouse or to be packed using AGV.

If the quality of a numbers of finished workpieces is not good, the manufacturing process of the product line will be interfered. According to [19], measuring the dimensional and geometric errors is carried out using laser interferometer, co-ordinate measuring machine (CMM), 3D probe ball bar system. CMM measures all the possible coordinates in a modelled component in X, Y, Z direction of related equipment, such as CNC. The results of measurements are the input of error correction algorithm and feedback to the CNC for finalizing the compensation and error corrections.

3 Background

3.1 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 behaviour to changing orders and operating conditions through self-optimization and reconfiguration" [11]. Industry 4.0 is being considered by the existence of several components interactions among interconnected devices i.e. sensors, actuators and computation services [10]. Essentially the data exchanged and produced in such interaction among several components establishes the underlying business processes for collaboration. With the huge amount of heterogeneous data generated and collected from the many connected devices such as sensors, processes and systems pose challenges as well as opportunities such as data driven discoveries such as analytics [12, 13].

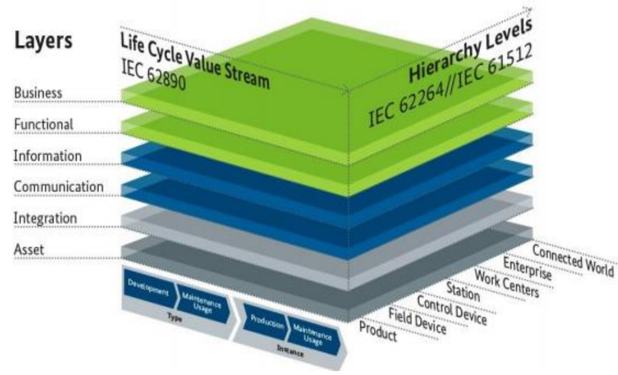

Figure 2: Reference Architecture Model Industry 4.0 [11]

Reference Architecture Model Industry (RAMI) 4.0 simplifies the fourth industrial revolution by providing a template with a three-dimensional model representing different complex components, sub-models and processes [11]. It comprises of hierarchy levels, architecture layers and lifecycle value stream. The hierarchy levels concern with the factory levels which includes collaborative organizations, factories, goods, devices, suppliers and customers (i.e. product, field device, control device, station, work centers, enterprise, and connected world) [11, 20]. The architecture layers represent six different components naming asset, integration, communication, information, functional and business and these components are essential to the development of system solutions for manufacturing network operations in a consistent manner [11]. The lifecycle value stream concerns with the value creation in the process of development and production in conjunction with maintenance usage. The value stream can be realized by the utilization of the constant data generated from the production lifecycle and the digitization of the whole development and market chain that offers opportunities for improvement of products, machines and other aspects [20]. At this stage, there remains a lack of coherent mapping and modelling of components, processes of RAMI 4.0 in manufacturing operations, specifically in real world implementation [10, 21].

3.2 FIWARE

FIWARE is an open source platform for building smart solutions gather data from many different sources (including but not limited to IoT) to build a “picture” of the real world and then process and analyse that information in order to implement the desired intelligent behaviour (which may imply changing the real world) [22]. There are five components, namely context processing, analysis and visualization at the top of Figure 3; core context management (context blocker) at the middle top of Figure 3; Internet of Things (IoT), robots and third-party systems at the bottom of Figure 3; data/API management, publication and monetization at the right of Figure 3; and development tools at the left of Figure 3.

Figure 3: FIWARE platform architecture overview [24]

1. Context processing, analysis and visualization of context information, bringing support to usage control and the opportunity to publish and monetize part of managed context data.
2. Core Context Management (Context Broker) allows to model manage and gather context information at large scale enabling context-aware applications with the FIWARE context information model [23, 24].
3. Internet of Things (IoT), robots and third-party systems, defines interfaces for capturing updates on context information and translating required actuations.
4. Data/API management, publication and monetization, implementing the expected smart behaviour of applications and/or assisting end users in making smart decisions.
5. Deployment tools support easing the deployment and configuration of FIWARE or third-party components and their integration with FIWARE Context Broker technology.

Different components map into FIWARE GEs [25], i.e. development of context-aware applications (Orion, STH-Comet, Cygnus, QuantumLeap, Draco); connection to the Internet of Things (IDAS, OpenMTC); real-time processing of context events (Perseo); handling authorization and access control to APIs (Keyrock, Wilma, AuthZForce, APInf); publication and monetization of context information (CKAN extensions, Data/API Biz Framework, IDRA); creation of application dashboards (Wirecloud); real-time processing of media streams (Kurento); business intelligence (Knowage); connection to robots (Fast RTPS, Micro XRCE-DDS); big data context analysis (Cosmos); cloud edge (FogFlow); documents exchange (Domibus).

With the constant development of IoT applications and devices, the ability to support not only open standards but also dynamic data becomes critical [26]. There is a need to gather and manage context information that allows the manufacturing process to be dynamic. The processing of that information and informing external actors, enables the information to actuate and therefore alter or enrich the current context in the context of modular and flexible manufacturing platform. FIWARE allows for a pick and mix approach in additional to its GE components, allowing the integration of other third platform components to design a hybrid platform.

The FIWARE context broker component is the core of the FIWARE platform [24]. It enables the system to perform updates and access to the current state of context. The Context Broker in turn is surrounded by a suite of additional platform components, which may be supply context data from diverse sources such as a CRM system, social networks, mobile apps or IoT sensors for example, supporting processing, analysis and visualization of data or bringing support to data access control, publication or monetization.

3.3 Industrial Data Space (IDS)

The Industrial Data Space (now International data space) is a virtual data space using standards and common governance models to facilitate the secure exchange and easy linkage of data in business ecosystems [27]. It thereby provides a basis for creating and using smart services and innovative business processes, while at the same time ensuring digital sovereignty of data owners [27]. The Industrial Data Space initiative was launched in Germany at the end of 2014 by representatives from business, politics, and research [28]. Meanwhile, it is an explicit goal of the initiative to take both the development and use of the platform to a Global level [28].

Data sovereignty is a central aspect of the International Data Spaces [27]. It can be defined as a natural person’s or corporate entity’s capability of being entirely self-determined with regard to its data [27]. It is also the base of building virtual factory or building a co-design and co-creation product platform. In compliance with common system architecture models and standards, the Reference Architecture Model uses a five-layer structure expressing various stakeholders’ concerns and viewpoints at different levels of granularity [27, 28]. The general structure of the Reference Architecture Model is illustrated in Figure 4 [27].

The model is made up of five layers: The Business Layer specifies and categorizes the different roles which the participants of the Industrial Data Spaces can assume, and it specifies the main activities and interactions connected with each of these roles [27].

The Functional Layer defines the functional requirements of the International Data Spaces, plus the concrete features to be derived from these [27]. The Process Layer specifies the interactions taking place between the different components of the Industrial Data Spaces; using the BPMN notation, it provides a dynamic view of the Reference Architecture Model [27]. The Information Layer defines a conceptual model which makes use of linked-data principles for describing both the static and the dynamic aspects of the Industrial Data Space's constituents [27]. The System Layer is concerned with the decomposition of the logical software components, considering aspects such as integration, configuration, deployment, and extensibility of these components [27].

In addition, the Reference Architecture Model comprises three perspectives that need to be implemented across all five layers: Security, Certification, and Governance [27].

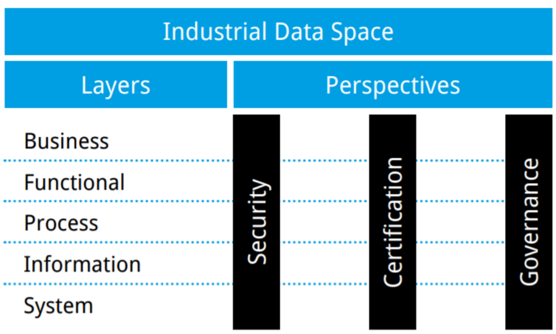

Figure 4: General Structure of Reference Architecture Model [27]

3.4 Blockchain

Blockchain is a distributed database, a technology platform for decentralized and transactional data sharing across a large network with connected users [29, 30]. A transaction can be any kind of value, money, goods, property, or votes. This transaction stores a timestamped list of blocks which record, share, and aggregate data that have ever recorded onto the blockchain network [30]. Cryptographic proofs make this data storage effectively tamper-proof [30]. Essentially, blockchain offers a decentralized, distributed and peer-to-peer transaction system across a network of users [29].

A Blockchain has some important features by design:

1. Decentralization: As being the nature of a decentralized platform, it removes the need for any third-party organization 'the middle-man' and hence enables the users to build trust with better transparency [31, 32].
2. Data integrity: All data stored in the Blockchain is hard to revise or tamper with [29, 33].
3. Transparency and auditability: The transactions conducted on the blockchain are transparent and allow for subsequent audits anytime [31].
4. Automation: Smart contracts are self-executing scripts [31], that can be stored and executed on the Blockchain, i.e. Ethereum Blockchain. This makes it possible to incorporate effects or to check conditions using smart contracts.

Besides, other design important ones are the differentiation between public and private choose and between permission-less and permissioned [34]. In a public Blockchain, anyone can join the network whereas in a private Blockchain only certain parties can join in the Blockchain network. In the same way, a permission-less Blockchain allows anyone to approve new blocks, i.e. for mining, whereas in a permissioned Blockchain, only certain parties can approve new blocks.

The concepts of blockchain are essential for business processes in this way: blockchain is a technology platform for decentralized and transactional data sharing across a network of untrusted participants. It enables the participants to find the shared state of transactions happened within the network without a central authority or any participant, and hence provides transparency and traceability of the truth [30, 35]. Cryptographic proofs make this data storage immutable.

Blockchain also offer a computational infrastructure to run smart contracts which can be executed by machines [30, 35]. Smart contracts can be used to implement business collaborations in general as well as inter-organizational business processes [9]. Untrusted parties can establish trust in the truthful execution of the code [5].

However, blockchain technology is still at an early stage of business adoption, especially from the perspective of technical challenges and limitations of the technology [35]. [29] summarizes seven of the technology's challenges and limitations: throughput, latency, size and bandwidth, security, wasted resources, usability, and versioning, hard forks and multiple chains. Furthermore, challenges such as scalability and manageability, i.e. conflict resolution need to be addressed.

3.5 Predictive Maintenance

The efficient management of maintenance activities is becoming essential to decreasing the costs associated with downtime and defective products [17], especially in highly competitive advanced manufacturing industries. This means that effective maintenance helps to keep the life cycle cost down and ensures expected operations.

Approaches to maintenance management can be divided into different groups which, in order of increasing complexity and efficiency [18], are as follows:

1. Run-to-Failure: where maintenance interventions are performed only after the occurrence of failures.
2. Preventive Maintenance: where maintenance actions are carried out according to a planned schedule based on time or process iterations.
3. Condition-based maintenance: when the actions on the process are taken after the verification of one or more conditions indicating a degradation of the process or the equipment.

4. Predictive Maintenance: where maintenance is performed based on an estimate of the health status of a piece of equipment [36]. Predictive Maintenance systems allow advance detection of pending failures and enable timely pre-failure interventions, utilizing prediction tools based on historical data, ad hoc defined health factors, statistical inference methods, and engineering approaches.

The development and applications of Internet of things i.e. smart devices, sensors, the increasing availability of huge data and cloud computing make the industry to be more effective in decision-making process [14, 16]. It offers opportunities to the industry to enhance capabilities such as monitoring, scheduling, maintenance management and quality improvement by the deployment of physical and virtual sensors enabling them to act ahead of time [18]. This means that a potential problem can be investigated before they arise in order to avoid or mitigate the impact of a future failure. Data-driven with machine learning approaches are recognized in providing the rising effective solutions in facilitating the decision-making process, assisted by the progressive capabilities of cloud computing, big data, machine learning, and analytics [14, 16]. However, there still exists several challenges in predictive maintenance and its data management due to the complexity and implementation, the capacity to manage big data with the nature of being dynamic and complex associations [16].

At this stage, there remains lack of a coherent Predictive Maintenance Platform in the manufacturing industry, particularly with RAMI 4.0 and FIWARE. Several conceptual frameworks for predictive maintenance have been proposed in the research community [37, 38, 39, 40, 41, 42, 43]. The most recent approach proposes a Predictive Maintenance based on RAMI 4.0, subsequently provided a case study based on the proposed solution [43]. However, several key factors should be considered in designing Predictive Maintenance Platform. These important factors include open collaborations based on industry open standards, the capability of modular design i.e. to easily act dynamically based on demands and needs (pluggable components). FIWRAE, open source framework with modular architecture can provide a solution responding to the complex and dynamic manufacturing environment.

4 IDS and Blockchain for Predictive Maintenance

4.1 IDS for Predictive Maintenance

In the development of Internet of things, manufacturing organizations are turning into data-driven approach in dealing with maintenance, particularly in the predictive aspect, to keep the life cycle cost down and ensure expected operations. Industrial big data enabled platforms as well as diverse data from both internal and external sources are essential to effectively implement the predictive capability [44]. Predictive maintenance management requires sharing data on production and inventory levels among networked partner firms, as well as the changing consumer demands [45]. Thus, it necessitates exploring the data sharing economy, sourcing data from different sources and providers such as external and data marketplaces, open data to enhance analytics.

In a complex and increasing competitive industries like manufacturing, collaborative business processes face several challenges such as data transparency, consistency and traceability [5, 9, 46]. For example, a typical collaboration in manufacturing chain, the certification of design and product quality and dynamically controlling production processes contribute to the problem domain of output deficiencies as well as leak of patent. IDS model facilitates secure data exchange by providing data sovereignty to data owners i.e. transparency of policy, data flow, usage and access across the parties [27, 28]. The IDS model provides a base model for the implementation of data sharing. Data sharing enhances decision making process, for example, by the usage of data from production sensors i.e. equipment, logistics, weather and traffic data in the analytics enables to plan effective production and distribution network [44]. Regarding predictive aspect, the implementation of IDS model can improve prediction results because data quality and consistency are maintained throughout its movement across multiple parties or systems. Most of all, the implementation of IDS model enables full data transparency i.e. traced with a high degree of trust, providing the data authority to the owner.

4.2 Blockchain for Predictive Maintenance

Blockchain as decentralized database ledger offers some benefits to the collaborative environment. This includes transparency, consistency, decentralization, traceability (auditability), and ownership [8]. IDS is a model architecture but does not provide any implementation details. Blockchain, being immutable database, has the potential to provide the implementation as transparent and traceable data storage. Blockchain offers greater control of data including originality, usage, enabling traceability with transparency and consequently enhance collaborations as well as trust. Predictive models based on machine learning requires ongoing retrain from new data, storing analytics models on blockchain can provide greater consistency due to temper-proof. Moreover, the quality of data enhances decision making by providing better analysis results derived from consistent data. Furthermore, blockchain as a decentralized database provides data access efficiently and quickly thus, enhancing real time monitoring more effective. For example, real-time monitoring for accessing the status of high value machines or tracking the progress of production.

4.3 Data Storing on Blockchain

Collaboration is typically facilitated by message exchange among multiple partners in which data is passed through the whole cycle of the collaborative business process [47, 48, 49]. The potential of storing certain data exchange on blockchain can improve collaboration in traditional as well as digital, smart or virtual factories, supporting the nature of dynamic collaboration and business opportunities, and dealing with trust among participants and traceability of process data [5, 9]. However, this requires the understanding of the nature of blockchain and the type of data to be stored in a business use case.

Regarding blockchain data, it offers immutable data in a decentralized manner, enabling the tracing of originality and time-stamped data [5, 9, 46]. However, it is critical to understand that data recorded on blockchain cannot be deleted, but permanently existed when recorded. It also means that blockchain data storage does not fully support the concept of CRUD (Create, Read, Update, Delete) but CRU. Thus, data required rules and compliance, i.e. data privacy, GDPR should be carefully managed (should not be stored) before implementation. This can apply to various use cases across industries. In addition, Blockchain is not optimized for performance and scalability, hence it lacks supporting IoT data, streaming unstructured data, big data [53]. Thus, the intended use case should be critically analyzed before implementing blockchain data storage.

In the context of BPM data, it exists several forms including BP model specification, business data for the process logic, execution states including histories, correlations among BP instances, and resources and their states [7]. These data are often scattered across databases and auxiliary data sources managed by the BPM systems including files i.e. BP schemas [6]. In addition to the traditional message exchange or database sharing for collaborative business process, modern collaborations require diverse data from different sources through the increasing development of data sharing economy across industries as well as the nature of dynamic collaboration and data. This demands new methods and technology to manage collaborative data.

Different domains have different types of data and some of the type of data can generally be grouped as follows [13, 16, 50];

1. Big data: very large and diverse datasets that include structured, unstructured data and semi-structured, from different sources in different volumes, that it is not impossible to handle by traditional databases and processes.
2. Structured, unstructured data and semi-structured: structured data normally refers to data with a pre-defined model storing in a traditional relational database whereas unstructured data such as audio, video, does not have a pre-defined model and semi-structured data such as JSON data has a structured form with no conventional conformance.
3. Time-stamped data: refers to a dataset that has a time ordering sequence of each data point i.e. the time of captured or collected.
4. Historical data: refers to historical data generated from systems, applications, etc.
5. Operational data: daily transaction data generated from business processes and systems.
6. Identity data: refers to the data of an object which can be used to identify the object.
7. Asset data: data that is "thing, item or entity that has actual or potential value" [51]. This data can cover several aspects of an organization, ranging from product data such as product design to machinery, etc.
8. Environment data: data relates to weather, temperature (dynamic temporal)

In the collaborative industrial context, data can accumulate from the following sources [2, 12, 13, 16, 50]:

1. Machine operation data, data from the control system, vibration, rotating, etc.
2. Condition data, such as the health condition or state of physical assets i.e. machine, equipment.
3. Monitoring (event) data, data such as fault (breakdown), system status (overhaul), installation (config), repair, oil change, etc.
4. Design data, data such as the product and machine design.
5. Product data: quality data such as the defective rate of each facility and usage data such as availability, repair rate.
6. Customer data, such as customer features, feedback data, suggestions.
7. Staff operation data, such as manual operation, working process
8. Cost data, such as cost of operations, tools, machines.
9. Logistics data
10. Environmental conditions, data such as weather, temperature, humidity, noises

In data-driven collaborative industry like Industry 4.0, data from different sources like data sharing is essential to the effective management of maintenance activities. This includes sharing information on production and inventory levels among networked partner firms, as well as ever changing consumer demands [37, 52]. Data which will provide value if stored on blockchain, may include data asset, machine data, time-stamped data, identity data. Keeping these data on blockchain enables data transparency, consistency as well as traceability, enhancing collaboration as well as analytics capabilities such as data consistency, real time monitoring.

4.4 Use Case Data Constraints Driven

The appropriate approach to deal with storing data on blockchain is using Use Case Data Constraints Driven approach. The steps include; 1) understand the use case for blockchain 2) identify blockchain data constraints 3) analyse and design blockchain data storage 4) implement and review. Initially, the use case with data constraints such as consistency, availability, immutability, privacy and protection, should be identified and evaluated. The analysis should include data value, data transparency and traceability to foster collaboration as well as value i.e. analytics, monetary. Based on the analysis, the type of data to be stored on blockchain should be recognized.

5 Predictive Maintenance Platform for the proposed application case

The Predictive Maintenance Platform architecture for the proposed application case is presented in Figure 5. It is designed in the context of RAMI 4.0 implementing the FIWARE platform with IDS and Blockchain. The platform architecture shows the core interactions among the main components through the definition of end-to-end integration and communication processes. The platform architecture is composed of three layers: Application Layer, Process Layer and Interface and Data Layer.

5.1 Application Layer

The application layer includes Graphical User Interface (GUI) that provides user options for different items including Overview of the Interface, Stream Data Analytics, Batch Data Analytics, Decision Support Analytics, Assessment such as equipment condition and status and System Repository such as equipment failure, status, code, etc. In the context of RAMI 4.0, the application layer represents the business layer (Interfaces, visualization, real time monitoring) and functional layer (decision making, assessment, tracing, etc.).

5.2 Process Layer

The FIWARE framework implements the process layer, integrating different modules and functionalities required for the predictive maintenance in the aspect of the functional layer in Industry 4.0. The core analytics of the predictive maintenance platform is the Cosmos big data analysis Generic Enabler, enabling big data analytics including batch (Cygnus) and streaming data (Spark) [22, 23, 24]. The Cosmos module takes care of analytics processing incorporating with data from sensor, HDFS, Craft DB, the platform DB, legacy data systems and shared data on blockchain. For advanced capabilities, Quatumleap for efficient time-series analytics and Complex event processing for real-time analytics are implemented. The process layer focuses on the functional layer of RAMI 4.0, representing the formal description of functions enabling the platform for horizontal integration of various functions [20].

5.3 Middleware and Data Layer

The Middleware and Data layer represents the event broker, adapters and the related data sources and storages. As the core component of the predictive maintenance platform, FIWARE Orion Context Broker manages the life cycle of the whole context information, ranging from registrations, updates, subscriptions and queries via NGSI APIs [22]. In the context of RAMI 4.0, the Orion context broker and IoT gateway represent the communication layer, data such as historical data, policy data, data usage represent the information layer, the shared blockchain data, IoT backend and sensor represents the integration layer, and the production equipment represents the asset layer.

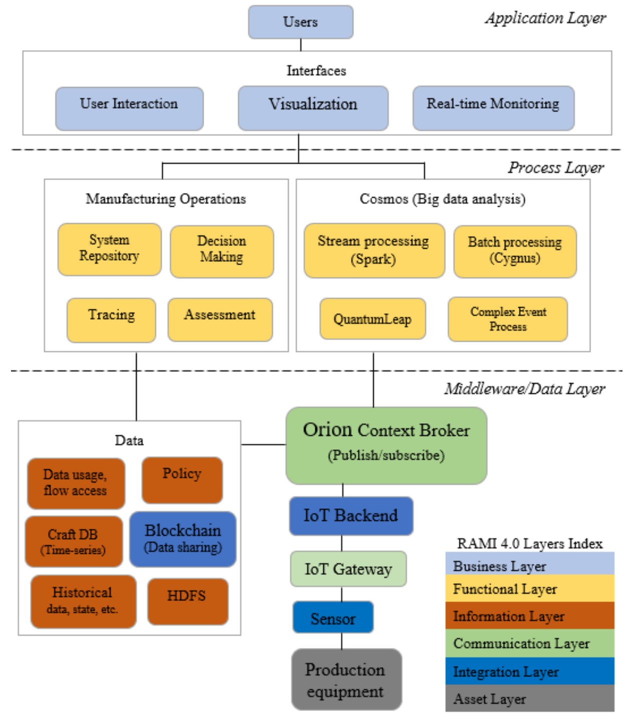

Figure 5: A RAMI 4.0 View Predictive Maintenance Platform based on FIWARE

5.4 Data Processing and Analytics

5.4.1 Data Source. Data required for the predictive maintenance are generally described in the following;

1. Production data: data such as product name, volume, product specification
2. Defect data: historical data about events occurred regarding fault or breakdown to the asset including the type of fault or breakdown, reason, time stamped
3. Maintenance/repair data: historical maintenance data of the assets including replacement, executed tasks
4. Machine data: historical operational data of the assets including status of the machine, state information such as the machine critical parameter name, parameter value, parameter value specification, up time, down time, alert indicator such as oil low
5. Asset manufacturer data: such as measurements, controls data (base data) from the manufacturer of the asset, storing on IDS blockchain [45].

The focus of predictive modelling in the case is the equipment condition based on equipment sensor data, manufacturer machine data from IDS blockchain data, historical machine conditioning data, fault., etc. The predictive maintenance is differentiated into two aspects: real-time analytics (alert and monitoring) and off-line predictive analysis.

5.4.2 Real-time Processing and Analytics. Real-time analytics concerns with real-time monitoring and notification. In this aspect, the underlying machines, devices and factories are considered as the maintenance items. As prerequisites, the item requiring maintenance for the alert indicator and key state information are derived from the characteristics of each item for the maintenance. During factory operation, real-time state data collected from the underlying machine is processed by comparing the key state of each maintenance item including the threshold. In this way, the process triggers the alert indicator if the threshold is met. The threshold of the item is based on a combination of events including geometric errors based on [19, 54]. The state and threshold of the equipment item represent a policy which is stored in the database. The policy can be triggered by an event from context broker or IDS connectors. The overall design architecture is presented in Figure 6.

In the real-time processing, the N_{item} represents the total number of items to be maintained. Real-time data collected from the underlying derives the state of N_{item}, representing the data value of the state information of each equipment item. The state threshold $N_{threshold}$ represents the threshold of each item’s state value. The alert [N_{item}] indicates the alert indicator (normal, abnormal) for each item. When the threshold is above the state threshold or the alert indicator is abnormal, the alert will trigger to the qualified available maintenance equipment to perform the executable maintenance task. Upon the completion of the maintenance task, the corresponding item of alert [N_{item}] is set to normal. If the maintenance task cannot solve the problem, the qualified available maintenance operator will be required, and the corresponding item of alert [N_{item}] will then also be set to normal.

5.4.3 Predictive Analysis (off-line). The predictive analysis off-line is based on the data-driven approach and predictive models which derived from historical data. Predictive analytics apply machine-learning algorithms to produce data-driven models of the asset. Predictive models utilize available variables and conditions that contributed to past events such as failures in order to predict future events (failures). New data are run through the model and the scores are generated on a real time basis. Predictive analytics encompasses a variety of techniques from statistics, modeling, machine learning, and data mining that analyze current and historical data to predict future events.

For a flexible and modular manufacturing system, the maintenance items usually need to be compatible with different processing components and different processing parameters. The traditional maintenance approach is typically manual, and the estimation of equipment life is usually based on production experience to decide when maintenance is required, or else wait for a failure alert of the components. This is expensive as well as tends to lead to a suspension in production, causing production cost. The remaining effective working time of the current equipment is predicted by combining its working status and historical information. Therefore, prediction algorithm can enhance the prediction accuracy for maintenance and production activities.

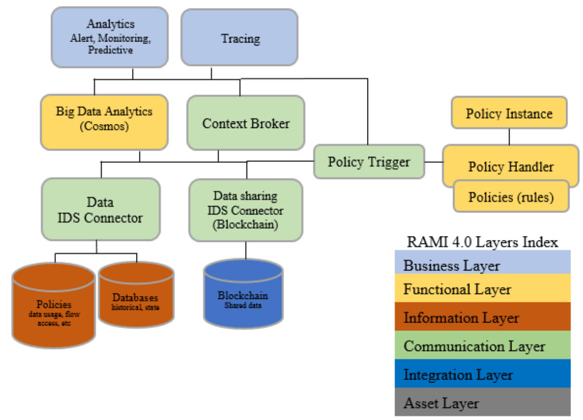

Figure 6: A RAMI 4.0 View Monitoring and Tracing Analytics based on FIWARE

The processing cycle typically involves four phases of processing:

1. Identifying phase: Identify the use case scenario
2. Modeling phase: Learn a model from training data
3. Predicting phase: Deploy the model to production and use that to predict the unknown or future outcome
4. Re-tuning phase: Review (repeat phase 2 – 3) based on new data and knowledge

Typically, predictive models used would be derived from machine learning algorithms such as Neural Networks, Decision Trees or Regression Analysis to arrive at conclusions [14, 15, 17, 18, 44, 55, 56, 57, 58, 59). For instance, SVM is a supervised learning method that can be used for classification and regression analysis [56]. In the binary classification, each sample is a record that belongs to the unit of time for an asset. In the context of regression, the aim is to find a model that calculates for example, the remaining useful life of each new sample as a continuous number [57]. It generally involves a training phase that requires machine condition (health) indicators with the corresponding label or equipment condition such as good, bad, fault [56, 57].

With the recent development of big data and cloud computing, neural networks have been widely used in machine learning models [57, 58, 59]. Neural network searches for patterns and interactions between features to automatically generate a best-fit model without a need for predefining features in the model [60]. In addition to predicting machine condition, neural network can also produce multiple classifiers, enabling optimizations such as optimal machine execution for a specific production, etc. The accuracy of trained models will determine the model to be deployed in production [14, 15, 18] and subsequently is stored in blockchain. The tracing aspect focuses on the ability to query a certain process data by a collaborative partner, enhancing transparent collaboration. In this aspect, process related data can be traced from blockchain data storage as well as other sources. Tracing can be described by the process instance ($Process_{inst}$) with related policies (Policy) and logs: T ($Process_{data}$) = {$Process_{inst}$, Policy, Log}.

6 Discussion

Industry collaborations in complex and dynamic manufacturing environment requires a concrete, extensible architecture and platform. Designing predictive maintenance architecture in the context of RAMI 4.0 with FIWARE framework requires the understanding of the industry operations, partners, communication and the underlying technologies. The complex interactions of industry partners and systems involve a variety of different range of applications and systems requiring different interaction schemes and mechanisms. The complexity of the industry can be simplified by the instantiation of RAMI 4.0 as shown in Figure 5. This enables better understanding about the interaction of complex processes and components with a high-level view. The instantiation of FIWARE components further provides a consistent Industry 4.0 manufacturing platform, enabling the integration and interoperability of the maintenance process with other operations, processes, technologies of the manufacturing environment in compliance with the Industry 4.0 standards. The open modular architecture of FIWARE enables the ease integration of different components as pluggable elements. On the other hand, FIWARE implementation is based on event driven approach which can pose challenges such as increased complexity, security risks.

The big data analysis enabled component of FIWARE in conjunction with both real-time and batch processing enables in dealing with big data collected from sensors as well as providing real-time monitoring based on the asset key state and threshold as presented in Figure 6. Implementing predictive models trained from different data sources such as historical operational and machine data as well as shared data such as manufacturer data via blockchain will provide better management of the condition and process of expensive manufacturing equipments and optimization of the whole production chain.

Collaboration with transparency and traceability is essential to the whole production chain in a complex and competitive industry like manufacturing. Thus, implementing the IDS connector as well as blockchain storage for data sharing with platform increases transparent collaboration. Asset manufacturing base data such as measurement, control data is considered as shared blockchain data and the implementation of the IDS connector deals with access policy and usage. The tracing enables querying the policies and usage of the shared data to the collaborative users, enabling transparent collaboration as well as future monetarization. However, data privacy and protection such as GDPR must be critically examined for any implementation.

7 Conclusion and Future Work

Flexible and consistent architecture platform is essential to modern industry collaborations like complex and dynamic manufacturing domain in order to effectively operate and manage the whole cycle of the production chain. In this paper, we proposed a Predictive Maintenance Platform designed with RAMI 4.0, providing a consistent view of the Industry 4.0 with different components and processes as shown in Figure 5. The instantiation of the FIWARE framework provides a modular open framework for the implementation of RAMI 4.0. Predictive maintenance capabilities provide effective ways to manage the conditions of equipment as well as optimizations of processes utilizing big data and machine leaning model enabled analytics. Collaborative business process requires maintaining transparency and traceable process data. Shared data storing on blockchain and accessed via IDS connector offer to be key enabler of transparency and traceability in complex and competitive collaborations.

In this paper, we focus on the design and instantiation of RAMI 4.0 and FIWARE framework, and we plan to do the implementation and evaluation of the design platform including real-time processing, predictive models, with the described application case as well as additional use cases across industries.

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REFERENCES

[1] Koren, Y., Gu, X., Guo, W., 2018. Reconfigurable manufacturing systems: Principles, design, and future trends, Font. Mech. Eng. 2018, 13(2); 121-136.
[2] Lee, J., Kao, H., Yang, S., 2014. Service Innovation and Smart Analytics for Industry 4.0 and Big Data Environment, Procedia CIRP Volume 16, 2014, Pages 3-8.
[3] Niehaves, B. and Plattfaut, R., 2011. Collaborative business process management: status quo and quo vadis. Business Process Management Journal, 17 (3), 384–402.
[4] Debevec, M., Simic, M., Herakovic, N., 2014. Virtual factory as an advanced approach for production process optimization, Int j simul model 13 (2014) 1, 66-78.
[5] Weber, I., Xu, X., Riveret, R., Governatori, G., Ponomarev, A., Mendling, J., 2016. Untrusted business process monitoring and execution using blockchain. In: Business Process Management - 14th International Conference, Proceedings (2016).
[6] van der Aalst, W. M. P., van Hee, K., 2004. Workflow Management: Models, Methods and Systems. MIT Press.
[7] Sun, Y., Su, J., Yang, J., 2016. Universal artifacts: a new approach to business process management (BPM) systems, Journal ACM Transactions on Management Information Systems (TMIS) TMIS Homepage archive Volume 7 Issue 1, March 2016 Article No. 3.
[8] Zyskind, G., Nathan, O., Pentland, A.S., 2015. Decentralizing Privacy: Using Blockchain to Protect Personal Data, 2015 IEEE Security and Privacy Workshops, 21-22 May 2015.
[9] Mendling, J., Weberb, I., van der Aalstd, W., vom Brockee, J., Cabanillasa, C., Danielf, F., Deboisg, S., Ciccioa, C. D., Dumash, M., Dustdari, S., Gal, A., Garca-Ba~nuelosh, L., Governatorib, G., Hullj, R., Rosal, M. L., Leopoldk, H., Leymannm, F., Reckerl, J., Reichertn, M., Reijersk, H. A., Rinderle-Mao, S., Rogge-Soltia, A., Rosemannl, M., Schultei, S., Singhp, M. P., Slaatsq, T., Staplesb, M., Weberr, B., Weidlichs, M, Wesket, M., Xub, X., Zhub, L., 2018. Blockchains for Business Process Management - Challenges and Opportunities, Journal ACM Transactions on Management Information Systems (TMIS), Volume 9 Issue 1, February 2018, Article No. 4.
[10] Thoben, K. D., Wiesner, S., Wuest, T.: “Industrie 4.0” and smart manufacturing-a review of research issues and application examples. International Journal of Automation Technol-ogy, 11(1), 4-16 (2017).
[11] Industry 4.0, 2016, Plattform Industries 4.0, RAMI 4.0 - a reference framework for digitalization [online] Available at: https://www.plattform-

i40.de/I40/Redaktion/EN/Downloads/Publikation/rami40-an-introduction.pdf?__blob=publicationFile&v=7 accessed on 04 September 2019.
[12] Groger, C., 2018. Building an Industry 4.0 Analytics Platform, Practical Challenges, Approaches and Future Research Directions, Datenbank-Spektrum, March 2018, Volume 18, Issue 1, pp 5–14.
[13] Lee, J., Ardakani, H. D., Yang, S., Bagheri, B., 2015. Industrial big data analytics and cyber-physical systems for future maintenance & service innovation, Procedia CIRP 38 (2015) 3 – 7.
[14] Provost, F., Fawcett, T.: Data Science and its relationship to Big Data and Data-Driven Decision Making, Big Data, Mary Ann Liebert, Inc. Vol.1 No.1 March (2013)
[15] Hashemian, H.M., Bean, W.C., 2011. State-of-the-Art Predictive Maintenance Techniques, IEEE Transactions on Instrumentation and Measurement (Volume: 60, Issue: 10, Oct. 2011) Page(s): 3480 – 3492
[16] Sang, G.M., Xu, L., de Vrieze, P., 2017. Simplifying Big Data Analytics Systems with a Reference Architecture. In: Camarinha-Matos L., Afsarmanesh H., Fornasiero R. (eds) Collaboration in a Data-Rich World. PRO-VE 2017. IFIP Advances in Information and Communication Technology, vol 506. Springer, Cham
[17] Mobley, R.K., 2002. An Introduction to Predictive Maintenance. Butterworth-Heinemann, 2002.
[18] Susto, G.A., Beghi, A., DeLuca, C., 2012. A predictive maintenance system for epitaxy processes based on filtering and prediction techniques. IEEE Trans. on Semiconductor Manufacturing, 25:638–649, 2012.
[19] Gohel, C.K. and Makwana, A.H., 2014. Integrated Geometric Errors Simulation, Measurement and Compensation of Vertical Machining Centres. Int J Adv Manuf Tech, 4(1), pp.21-26.
[20] Zezulka, F., Marcon, P., Vesely, I., Sajdl, O., 2016. Industry 4.0 – An Introduction in the phenomenon, IFAC-PapersOnLine Volume 49, Issue 25, 2016, Pages 8-12.
[21] Hankel M, Rexroth B., 2015. The Reference Architectural Model Industrie 4.0 (RAMI 4.0). 2015, ZVEI.
[22] FIWARE Developers (2019) [online] Available at: https://www.fiware.org/developers/ last accessed 20 August 2019.
[23] FIWARE Academy (2019) [online] Available at: https://fiware-academy.readthedocs.io/en/latest/ last accessed 31 July 2019.
[24] FIWARE Catalogue, (2019) [online] Available at: https://www.fiware.org/developers/catalogue/ last accessed 20 August 2019.
[25] Fox, J. (2019) FIWARE Overview [online] Available at: https://www.slideshare.net/FI-WARE/fiware-wednesday-webinars-fiware-overview last accessed 31 July 2019.
[26] Kovacs, E., Bauer, M., Kim, J., Yun, J., Gall, F. L., Zhao, M., 2016. Standards-based World-Wide Semantic Interoperability for IoT, IEEE Communications Magazine, Volume: 54, Issue: 12, December 2016.
[27] Otto, Boris, et al. "Reference architecture model Version 3.0." International Data Space Association https://www.internationaldataspaces.org/publications/reference-architecture-model-3-0, last accessed 2019/08/12 (2019).
[28] Otto, Boris, et al. "Industrial Data Space: digital sovereignty over data" https://www.fraunhofer.de/content/dam/zv/en/fields-of-research/industrial-data-space/whitepaper-industrial-data-space-eng.pdf last accessed 2019/08/13 (2016).
[29] Swan, M, 2015. Blockchain, A Blueprint for a New Economy. CA: O'Reilly Media, Inc.
[30] Crosby, M, Nachiappan, Pattanayak, P., Verma, S., Kalyanaraman, V., 2016. BlockChain Technology: Beyond Bitcoin. Applied Innovation Review, Issue No. 2 June 2016.
[31] Christidis, K., Devetsikiotis, M., 2016. Blockchains and Smart Contracts for the Internet of Things, The Plethora of Research in Internet of Things (IoT) Volume 4: 2016.
[32] Porru, S., Pinna, A., Marchesi, M., Tonelli, R., 2017. Blockchain-Oriented Software Engineering: Challenges and New Directions, 2017 IEEE/ACM 39th International Conference on Software Engineering Companion (ICSE-C), 20-28 May 2017.
[33] Fanning, K., Centers, D.P., 2016. Blockchain and Its Coming Impact on Financial Services.
[34] Beck, R., Muller-Block, C., 2017. Blockchain as Radical Innovation: A Framework for Engaging with Distributed Ledgers as Incumbent Organization.
[35] Beck, R., Czepluch, J. S., Lollike, N., Malone, S., 2016. Blockchain – The Gateway To Trust-free Cryptographic Transactions. Research Papers. 153.
[36] Krishnamurthy, L., Adler, R., Buonadonna, P., Chhabra, J., Flanigan, M., Kushalnagar, N., Nachman, L., Yarvis, M., 2005. Design and deployment of industrial sensor networks: Experiences from a semiconductor plant and the north sea. In SenSys, 2005.
[37] Wang, J., Zhang, L., Duan, L., Gao, R.X.: A new paradigm of cloud-based predictive maintenance for intelligent manufacturing. J. Intell. Manuf. 28(5), 1125–1137 (2017).
[38] Hribernik, K., von Stietencron, M., Bousdekis, A., Bredehorst, B., Mentzas, G., Thoben, K.D.: Towards a unified predictive maintenance system-a use case in production logistics in aeronautics. Procedia Manuf. 16, 131–138 (2018).
[39] Voisin, A., Levrat, E., Cocheteux, P., Iung, B.: Generic prognosis model for proactive maintenance decision support: application to pre-industrial e-maintenance test bed. J. Intell. Manuf. 21(2), 177–193 (2010)
[40] Peng, Y., Dong, M., Zuo, M.J.: Current status of machine prognostics in condition-based maintenance: a review. Int. J. Adv. Manuf. Technol. 50(1–4), 297–313 (2010).
[41] Guillén, A.J., Crespo, A., Gómez, J.F., Sanz, M.D., 2016. A framework for effective management of condition based maintenance programs in the context of industrial development of E-Maintenance strategies Comput. Ind., 82 (2016), pp. 170-185
[42] Engel, Y., Etzion, O., Feldman, Z., 2012. A basic model for proactive event-driven computing, Proceedings of the 6th ACM International Conference on Distributed Event-based Systems, ACM (2012), pp. 107-118.
[43] Bousdekis, A., Lepenioti, K., Ntalaperas, D., Vergeti D., Apostolou, D., Boursinos, V., 2019. A RAMI 4.0 View of Predictive Maintenance: Software Architecture, Platform and Case Study in Steel Industry, International Conference on Advanced Information Systems Engineering CAiSE 2019: Advanced Information Systems Engineering Workshops pp 95-106.
[44] Wan, J., Tang, S., Shu, Z., Li, D., Wang, S., Imran, M., Vasilakos, A. V., 2016. Software-Defined Industrial Internet of Things in the Context of Industry 4.0 IEEE Sensors Journal (Volume: 16, Issue: 20, Oct.15, 2016).
[45] Matsubara, A., & Ibaraki, S. (2009). Monitoring and control of cutting forces in machining processes: A review. International Journal of Automation Technology, 3(4), 445–456.
[46] Sikorski, J. J., Haughton, J., Kraft, M., Street, P., Drive, P. F., 2016. Blockchain technology in the chemical industry: machine-to-machine electricity market, Appl. Energy, vol. 195, no. 178, pp. 234-246, Jun. 2016.
[47] van der Aalst, W., 2000. "Process-oriented architectures for electronic commerce and interorganizational workflow", Information Systems, vol. 24, no. 8, pp. 639-671, 2000.
[48] Chen, Q., Hsu, M., 2001. Inter-enterprise collaborative business process management, Proceedings 17th International Conference on Data Engineering 2-6 April 2001.
[49] Fdhila, W., Rinderle-Ma, S., Knuplesch, D., Reichert, M., 2015. Change and compliance in collaborative processes. In IEEE SCC, pages 162–169, 2015.
[50] Zhang, Y., Ren, S., Liu, Y., Si, S., 2017. A big data analytics architecture for cleaner manufacturing and maintenance processes of complex products, Journal of Cleaner Production Volume 142, Part 2, 20 January 2017, Pages 626-641.
[51] ISO 55000 (2014) [online] Available at: https://www.iso.org/obp/ui/#iso:std:iso:55000:ed-1:v2:en last accessed 26 August 2019.
[52] Sundararajan, A, 2014. Peer-to-peer businesses and the sharing (collaborative) economy: Overview, economic effects and regulatory issues, Written testimony for the hearing titled The Power of Connection: Peer to Peer Businesses, January.
[53] Makhdoom, I., Abolhasan, M., Abbas, H., Ni, W., 2019. Blockchain's adoption in IoT: The challenges, and a way forward, Journal of Network and Computer Applications Volume 125, 1 January 2019, Pages 251-279.
[54] Soori, M., Arezoo, B., Habibi, M., 2013. Dimensional and geometrical errors of three-axis CNC milling machines in a virtual machining system, Computer-Aided Design · November 2013.
[55] Yan, J., Meng, Y., Lu, L., Li, L., 2017. Industrial Big Data in an Industry 4.0 Environment: Challenges, Schemes, and Applications for Predictive Maintenance, Complex System Health Management based on Condition Monitoring and Test Data, IEEE Access (Volume:5), Page(s): 23484 – 23491.
[56] Chang, C., Lin, C., 2011. LIBSVM: A library for support vector machines, Journal ACM Transactions on Intelligent Systems and Technology (TIST) archive Volume 2 Issue 3, April 2011 Article No. 27.
[57] Yan, H., Wan, J., Zhang, C., Tang, S., Hua, Q., Wang, Z., 2018. Industrial Big Data Analytics for Prediction of Remaining Useful Life Based on Deep Learning, Real-Time Edge Analytics for Big Data in Internet of Things, IEEE Access (Volume:6), Page(s): 17190 – 17197.
[58] Lee, K.B., Cheon, S., Kim, C.O., 2017. A Convolutional Neural Network for Fault Classification and Diagnosis in Semiconductor Manufacturing Processes, IEEE Transactions on Semiconductor Manufacturing (Volume: 30, Issue: 2, May 2017) Page(s):135-142.
[59] Lin, C.C., Tseng, H.Y., 2005. A neural network application for reliability modelling and condition-based predictive maintenance, The International Journal of Advanced Manufacturing Technology, January 2005, Volume 25, Issue 1–2, pp 174–179.
[60] Gao, J. (2019), Machine Learning Applications for Data Center Optimization, Google, [online] Available at: https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/42542.pdf last accessed 20 September 2019.