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 application of Internet of things, i.e. smart devices and sensors increases collection and availability of diverse data. Advanced technologies such as big data analytics and cloud computing offer new opportunities for effective optimization of 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 RAMI 4.0 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.

CCS Concepts
•Applied computing→Enterprise computing→Business process management→Cross-organizational business processes •Applied computing.

Keywords
Predictive maintenance; Industry 4.0; FIWARE; Industrial data space; Blockchain; Collaborative business process

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1. INTRODUCTION
Being widely adopted by industry, Business Process Management (BPM) facilitates the formal approach in dealing with the analysis, improvement and management of business processes. However, BPM faces new challenges, and process models focused on the control flow become ineffective. The dynamic nature of market demands, competitions and globalization, the short life cycle of product force organizations to work beyond its boundary including machines/devices collaboration [27, 32, 39]. This demands enterprises with different business interests and competitiveness to work together for a defined business goal [39].

Collaboration enables multiple partners to produce a common business goal by integrating their agreed business process [39]. Traditional manufacturing i.e. physical machines, equipment, etc. are slow, long process, expensive as well as inefficient in dealing with the challenges created by the short product lifecycle, dynamic nature of market demands, competitions and globalization [27]. To effectively manage the demands and life cycle of production, business processes collaboratively are managed and operated across different enterprises and factories [10, 27]. For instance, in the context of virtual enterprise manufacturing, virtual factory enables the creation of new business ecosystems by integrating business processes across different enterprises for the simulation, modelling, testing of different design options, performance evaluation and efficiency of time-to-production [10].

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 functioning cross-organizational business processes seamlessly and flexibly [10]. In this aspect, organizations can collaborate business functions through different devices with the required data, facilitating instant collaboration among collaborative partners [10]. On the other hand, this brings challenges such as trust and transparency among collaborative participants [60]. Traditional collaborative business processes typically operate by exchanging messages between different partners via web services or sharing a collaborative database [1, 51]. These collaborations are often based on the centralized approach, which requires an authorized agent and subsequently poses challenges such as trust and traceability [60].

As data storage, blockchain has the potential to offer 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 [4, 8, 9, 37, 60]. However, blockchain technology platform still poses several key challenges including scalability, performance, security and business use cases [37, 60, 65]. One important approach to tackling these challenges is to take advantage of blockchain as data asset approach, rather than running collaborative business processes entirely.

Modern industrial computing is advancing to focus on the concept of Industry 4.0 [55]. Industry 4.0 is recognized as the value-creating network established by the flexibility and utilization of emerging advanced technologies such as Internet of things, Cyber Physical Systems, etc. In this aspect, plants and machines are empowered with the ability to adapt their operations and operating conditions such as self-optimization and reconfiguration using advanced capabilities such as autonomous tasks derived from deep learning techniques [42]. Basically, the fundamental business processes for collaboration are facilitated by the several components which interact and exchange data.

Effective maintenance is critically important to modern collaborative manufacturing. It can have impact on the collaboration chain due to the costs associated with faulty product and downtime [38]. Traditional corrective and preventive maintenance approaches cannot meet the requirements of modern collaborative manufacturing due to cost and complexity [56]. Thus, a new approach is needed to offer a flexible maintenance platform solution which supports predictive maintenance complying the Industry 4.0 standards and enabling effective optimization of maintenance and production process and reducing downtime and cost.

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

2. APPLICATION CASE FOR PREDICTIVE MAINTENANCE

Production machine equipment tools become important assets of the manufacturing. Any failure or deficient process of a factory component can have an impact for an entire production line, resulting unplanned downtime and costs [38, 53]. Conventional maintenance approach e.g. manual maintenance is inefficient and cumbersome in collecting machine equipment data due to the general concern of trust, discrete support and limited data available from competitive equipment manufacturers. Internet of things such as RFID/sensor technology enables to collect a huge amount of data but the process is complex, and it is impractical for conventional data processing and tools to producing intelligent information [45–48].

The constant collection of huge data and its usage from the equipment can offer new opportunities for analytics. It can facilitate a better way of operating maintenance plan and activity [38, 53]. Ultimately, it enables the ability to optimize the machine equipment's operation and condition, and identity potential problems in advanced and carry out an appropriate maintenance task in a predictive manner. For an effective maintenance decision making, new method is required to integrate various data from different sources and domains. Typically, factory machine functional, operational and production data, including sensor data are all essential for the analysis and development of models for a failure or an inefficient process prediction.

A flexible manufacturing factory typically involves several different systems. It can range from processing system, systems such as logistics, auxiliary to different information systems. A flexible factory case is illustrated in Figure 1. The processing system in this case operates with four sets of equipment, robots, automatic stereoscopic warehouse, numbers of AGV trolleys and carrier plates. Furthermore, To process the operation of the workpiece, different machines such as coordinate measuring machine (CMM) for operations i.e. measurement, cleaning and drying are utilized for the factory.

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 in various involved equipment. 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. Using co-ordinate measuring machine (CMM), 3D probe ball bar system and laser interferometer, dimensional geometric errors can be measured [20]. For instance, CMM is used for measuring the coordinates of a component in X, Y, Z direction of associated machine tool such as CNC. The unqualified artefact could cause by wearing cutting tools or equipment. If the cutting tools are fine, 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

Modern industrial computing is advancing to focus on the concept of Industry 4.0 [55]. Industry 4.0 is recognized as the value-creating network established by the flexibility and utilization of emerging advanced technologies such as Internet of things, Cyber Physical Systems, etc. In this aspect, plants and machines are empowered with the ability to adapt their operations and operating conditions such as self-optimization and reconfiguration using advanced capabilities such as autonomous tasks derived from deep learning techniques [42]. Industry 4.0 thus can be considered by the existence of several components interactions among interconnected devices i.e. sensors, actuators and computation services [55]. Essentially, the fundamental business processes for collaboration are facilitated by the various components which interact and exchange data. With the huge amount of heterogeneous data generated and collected from the many connected devices such as sensors, processes and systems pose challenges and opportunities i.e. data-driven analytics [21, 30, 46–48].

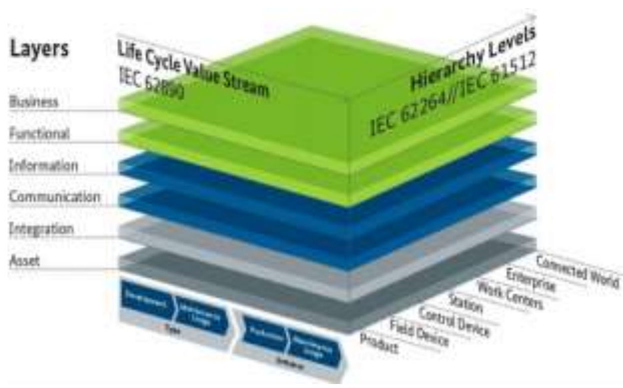

Figure 2: Reference Architecture Model Industry 4.0 [11]

Reference Architecture Model Industry (RAMI) 4.0 simplifies the fourth industrial revolution (Industry 4.0) by a three-dimensional model representing different complex components, sub-models and processes [42]. The model consists of architecture layers, hierarchy levels and lifecycle value stream. The hierarchy levels concern with the factory levels which include collaborative organizations, factories, goods, devices, suppliers and customers e.g. field and control device, enterprise, product and connected world [42, 63]. The architecture layers represent six different components; asset, integration, communication, information, functional and business. These components are essential to the development of system solutions for manufacturing network operations in a consistent manner [42]. 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 entire development and market chain that offers opportunities for optimizations such as products, systems, machines, etc. [63]. 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 [23, 55].

3.2 FIWARE

FIWARE exists as an open source platform/framework intended for developing different smart industrial solutions which collect data from many different sources to process and analyse that information in order to implement intelligent behaviours and support decision making process [16].

Figure 3: FIWARE platform architecture overview [24]

FIWARE has five components:

- *Context processing, analysis and visualization* for supporting smart decision making and different applications.
- *Core Context Management (Context Broker)* for managing context information at large scale enabling context-aware applications with context information model [14, 15].
- *Internet of Things, robots and third-party systems* for supporting the integration and interaction of context information and translating required actuations.
- *Data/API management, publication and monetization* for supporting the publication and monetization of context data and its usage control.
- *Deployment tools* for supporting the general implementation of FIWARE and different components including third-party components.

Different components map into FIWARE generic enablers (GEs) [17], i.e. development of context-aware applications such as Orion context broker, Cygnus; complex event processing of context events e.g. Perseo; management of access and control to APIs such as AuthZForce, Keyrock; the Internet of Things connection e.g. IDAS, OpenMTC; cloud edge e.g. FogFlow; robots connection such as Fast RTPS, Micro XRCE-DDS; publication and monetization of context data such as Data/API Biz Framework, CKAN, IDRA; utilization of application dashboards such as Grafana; real-time processing of media streams e.g. Kurento; big data context analysis e.g. Cosmos; business intelligence e.g. Knowage; documents exchange e.g. Domibus.

With the constant development of IoT applications and devices, the ability to support not only open standards but also dynamic data becomes critical [28]. Context information is essential to facilitating the manufacturing process to be dynamic. In this aspect, the processing of context information which interacts with different actors, brings better capturing and understanding of the current context of flexible manufacturing platform. In addition to its GE components, FIWARE supports a pick and mix approach, allowing the integration of different third party platform and components to develop a hybrid platform solution.

The FIWARE context broker is essential to implementing the FIWARE framework [15]. It enables the core interaction between different components and the system including updates and access to the current state of context. In this sense, the context broker is interacted with context data derived from diverse sources such as Logistics, ERP, mobile and IoT devices for processing, analysis and visualization of data as well as supporting data access control, publication and monetization.

3.3 Industrial Data Space (IDS)

Industrial Data Space (now International data space) was initiated by a group of representatives from business, politics and research in Germany in 2014 [18, 40]. It aims to promote the development and adoption of the platform to globally [18]. The Industrial Data Space exists as a virtual data space which accommodates data exchange between different stakeholders in the business ecosystems using common governance models and standards. [40]. IDS facilitates a basis for collaborative services and business processes which ensures the digital sovereignty of data owners [40]. Data sovereignty can be described as an entity's e.g. person or corporate capability of being entirely self-determined regarding its data [40]. In a collaborative manufacturing, IDS is essential to establishing a virtual factory including collaboration product platform such as co-design, co-creation. IDS is facilitated by the Reference Architecture Model using common system architecture models and standards. It also considers different concerns and viewpoints from the various stakeholders at different granular levels [18, 40]. The general structure of the Reference Architecture Model is presented in Figure 4 [40].

The Business Layer concerns with specifying the main activities and categorizing different roles and interactions of the participants in the Industrial Data Spaces [40]. The Functional Layer states the functional requirements of the International Data Spaces, including concrete features [40]. The interactions of the different components in the Industrial Data Spaces is facilitated by the Process Layer [40]. To assist in dealing with the dynamic and static aspects of IDS's participants, a conceptual model is provided by the Information Layer using linked-data principles [40]. The aspect of dealing with logical software component decomposition regarding integration, configuration, deployment, and extensibility is handled by the System Layer [40].

Furthermore, the perspectives of Security, Certification and Governance need to be managed and implemented across all five layers: [40].

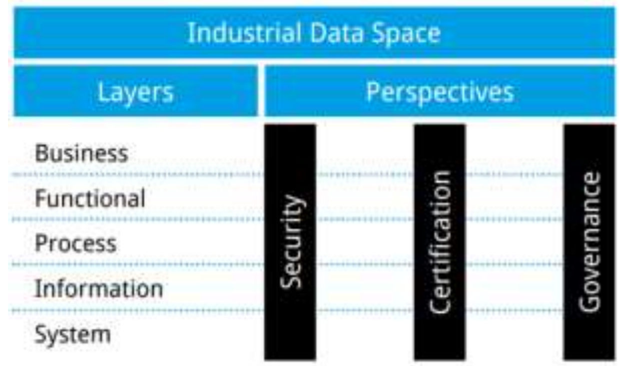

Figure 4: General Structure of Reference Architecture Model [27]

3.4 Blockchain

Blockchain is a distributed database and operates as a technology platform for decentralized and transactional data sharing across a network with connected users [9, 54]. A transaction can be any kind of value, money, goods, property, or votes. It keeps a timestamped list of blockchain data i.e. transactions that have ever stored onto the blockchain network [9]. Cryptographic proofs make this data storage effectively tamper-proof [9]. Essentially, blockchain offers a decentralized, distributed and peer-to-peer transaction system across a network of users [54].

A Blockchain has some important features by design:

- Decentralization: better trust and transparency among users can be achieved via a decentralized platform as it removes the need for any third-party organization [8, 43].
- Data integrity: blockchain data is difficult to tamper with [12, 54].
- Transparency: due to its decentralized approach and data integrity, blockchain transactions are transparent [8].
- Auditability: transparent transactions with data integrity within a decentralized platform enables audits anytime [8].
- Smart contract: Smart programs or contracts can be automatically executed and stored on the Blockchain [8]. Smart contracts further allow condition checks for different business rules.

Besides, critical design choices such as public or private, permission-less or permissioned are available for implementation [3]. Generally, by adopting a private and permissioned approach, only certain participants can join and approve new block i.e. mining in the Blockchain network. On the other hand, public or permissioned-less approach generally allows anyone to join and process mining in the network.

In the context of collaborative business process, the concept of blockchain can offer opportunities for enhancing the collaboration. Blockchain is a technology platform for decentralized and transactional data sharing across a network of untrusted participants. This means that the participants can obtain the shared state of transactions happened within the network without a central authority or any participant. Thus, it provides transparency and traceability of the truth [3, 9]. Cryptographic proofs make this data storage immutable. Blockchain also offers a computational infrastructure to run smart contracts which can be executed by machines [3, 9]. Moreover, general business collaborations, and collaborative business processes can be implemented by smart contracts [37]. This facilitates trust collaborations i.e. truthful execution of code for the untrusted parties [60].

However, blockchain technology still faces different technical challenges, limitations of the technology and business adoption [3]. [54] summarizes different technology challenges and limitations including multiple chains, security, size, throughput, latency and bandwidth. Furthermore, challenges such as scalability and manageability, i.e. conflict resolution need to be addressed.

3.5 Predictive Maintenance

Maintenance is directly associated with reducing the costs related with downtime and defective products [38] in the manufacturing industries. This means that effective maintenance helps to keep the life cycle cost down and ensures expected operations.

Maintenance management approaches can be distinguished into different groups based on complexity and efficiency [53], are as follows:

- Corrective maintenance: maintenance is carried out upon failures.
- Preventive maintenance: maintenance activities are performed based on a scheduled plan or iteration.
- Condition-based maintenance: maintenance actions are performed after a condition degradation of the process or equipment is indicated.
- Predictive Maintenance: maintenance is carried out based on an estimation of the health status of an equipment [29]. Predictive Maintenance systems facilitates advanced detection of potential problems and act on appropriate actions, utilizing predictive analytics and tools utilizing historical data, condition factors, statistical and engineering methods.

The development and applications of Internet of things i.e. smart sensor devices, the increasing availability of huge data and cloud computing facilitate the industry to be more effective in decision making process [38, 44, 46–48]. It offers opportunities to the industry to enhance capabilities such as monitoring, maintenance management, scheduling and quality improvement by the deployment of physical and virtual sensors enabling to act ahead of time [53]. This means that a potential problem can be investigated before they arise in order to avoid a future failure. Data-driven approaches supported by the capabilities of big data, machine learning, analytics and cloud computing are recognized in facilitating effective decision making process [44, 46–48]. However, there exist several challenges in predictive maintenance and its data management and complexity [48].

At this stage, there remains lack of a coherent Predictive Maintenance Platform in the manufacturing industry, particularly with RAMI 4.0 and FIWARE. Different approaches for predictive maintenance have been explored [5, 11, 22, 25, 31, 41, 57, 59]. Recently, Bousdekis et al. [5] proposed a Predictive Maintenance based on RAMI 4.0, subsequently provided a case study based on the proposed solution. 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 offer 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 and diverse data from both internal and external sources are essential to implementing effective predictive capability [58]. Data about production, inventory levels as well as demands among networked partners are important for the management of predictive maintenance [36]. 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 manufacturing industry, collaborative business processes face several challenges such as data transparency, consistency, interoperability and traceability [37, 49, 60, 61]. For example, a typical collaboration in manufacturing chain, the certification of quality about design and product, and the operation of 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 data policy, usage and access across the parties [18, 40], and a base model for data sharing implementation. 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 [58]. 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

As a decentralized database, blockchain offers some benefits to the collaborative environment. This includes transparency, consistency, decentralization, traceability (auditability), and ownership [65]. IDS is a model architecture but does not provide any implementation details. Blockchain, being immutable database, has the potential to provide an implementation solution supporting 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. Also, 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 Storing Data on the 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 [2, 7, 13]. 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 [37, 60]. 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 [37, 49, 60]. 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 it only supports the CRU aspect. 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 [35]. 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 business process (BP) model specification, business data for the process logic, execution states including historical logs, correlations among BP instances, and resources and their states [51]. These data are often disseminated across databases and additional data sources managed by the BPM systems including files i.e. BP schemas [1]. 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 [30, 48, 64]:

- 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.
- 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.
- 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.
- Historical data: refers to historical data generated from systems, applications, etc.
- Operational data: daily transaction data generated from business processes and systems.
- Identity data: refers to the data of an object which can be used to identify the object.
- Asset data: data that is "thing, item or entity that has actual or potential value" [26]. This data can cover several aspects of an organization, ranging from product data such as product design to machinery, etc.
- Environment data: data relates to weather, temperature (dynamic temporal)

In the collaborative industrial context, data can accumulate from the following sources [21, 30, 32, 48, 64]:

- Machine data: operation data such as control system, vibration, rotating, etc.
- Condition data: such as the health condition or state of physical assets i.e. machine, equipment.
- Monitoring (event) data: data such as fault (breakdown), system status (overhaul), installation (config), repair, oil change, etc.
- Product data: about quality, usage, etc.
- Design data: about product, machine, parts, etc.
- Customer data: features, feedback, suggestions.
- Staff operation data: working process, manual operation
- Cost data: costs regarding operations, tools and machines.
- Logistics data
- Environmental data, data such as weather, temperature, humidity, noises, etc.

In Industry 4.0 data-driven collaborative industry, data sharing i.e. data from different sources is essential to the effective management of maintenance activities. This includes sharing data on production inventory levels among networked partner firms, and demands [52, 59]. 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 Proposed Use Case Data Constraints Driven Method

In this work, a novel method is established for assisting in dealing with storing data on the blockchain. The approach is called Use Case Data Constraints Driven which primarily focuses on identifying the use case and data constraints related to blockchain adoption. The approach includes four steps; 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 store on blockchain is to be realized. At this stage, the initial steps of the approach are generally established in order to satisfy current requirements, and further work including formal framework and usage will be carried out in the next future work.

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 demonstrates the core interactions between the different components by the definition of end-to-end integration and interaction processes. The design platform architecture is composed of three layers: Application Layer, Process Layer, and Middleware and Data Layer.

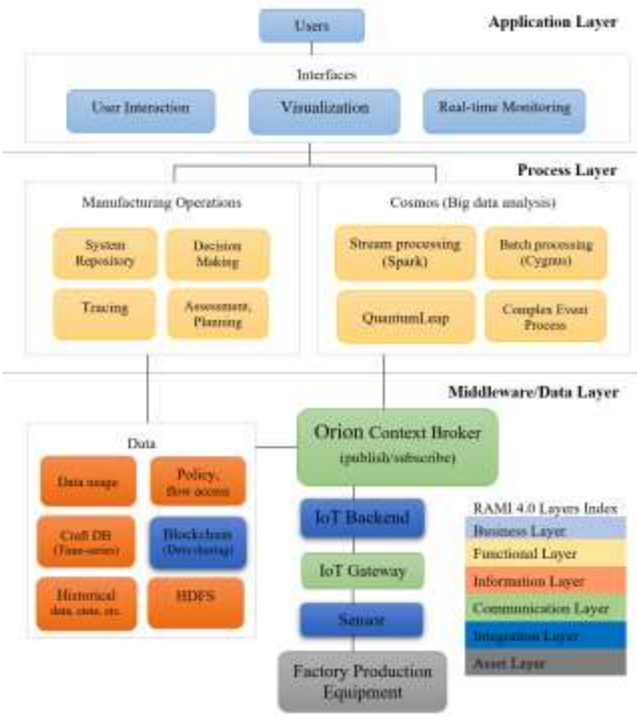

Figure 5: A RAMI 4.0 Predictive Maintenance Platform based on FIWARE

5.1 Application Layer

The application layer includes Graphical User Interface (GUI) that provides user options for different items including Overview of the Interface, Big Data Analytics including streaming and batch data processing, Decision Support Analytics, Assessment and Planning such as equipment condition, status, maintenance plan, 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, schedule plan, tracing, etc.).

5.2 Process Layer

The FIWARE framework implements the process layer, composing the modules and functionalities needed for the predictive maintenance in the context of the functional layer of RAMI 4.0. The main analytics component of the predictive maintenance platform is the Cosmos Generic Enabler which enables Big Data analytics including streaming and batch data processing [14–16]. 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 covers the functional layer of RAMI 4.0 which represents the different description of various functions supporting horizontal integration of various functions [63].

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 [16]. 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 factory production equipment represents the asset layer.

5.4 Data Processing and Analytics

5.4.1 Data Source

Data required for the predictive maintenance are generally described in the following:

- Production data: data such as product name, volume, product specification
- Defect data: historical data about events occurred regarding fault or breakdown to the asset including the type of fault or breakdown, reason, time stamped
- Maintenance/repair data: historical maintenance data of the assets including replacement, executed tasks
- Machine data: historical operational data of the assets including status of the machine, state information such as the name and value of the machine critical parameter and related specification, up time, down time, alert indicator such as oil low
- Asset manufacturer data: such as measurements, controls data (base data) from the manufacturer of the asset, storing on IDS blockchain [36].

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 notification and monitoring. In this aspect, the considered maintenance items are derived from the key components i.e. machines, tools, etc. 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. Real-time data about the key components is being collected and processed during operation, determining the key state and threshold of each item. 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[20, 50]. 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.

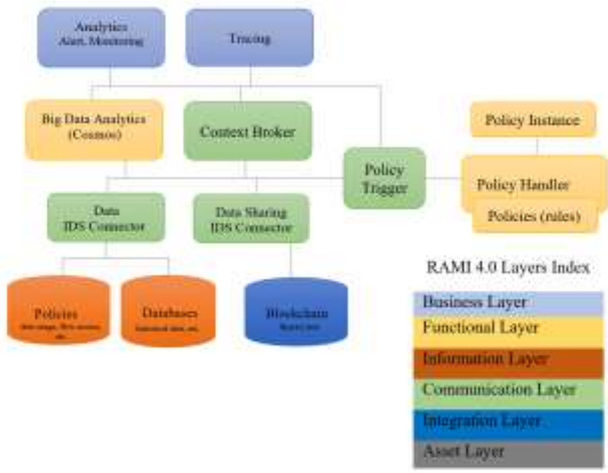

Figure 6: A RAMI 4.0 View Monitoring and Tracing Analytics based on FIWARE

For real-time processing, the number of critical equipment items, N_{item} is identified for maintenance. Real-time data captured from the equipment components determines the state of N_{item}, representing the state information, i.e. data value of each equipment item. The state threshold $N_{threshold}$ signifies the threshold of each item's state value. The alert N_{item} indicates the alert indicator (normal, abnormal) for each equipment item. When the threshold is above the state threshold or the alert indicator is abnormal, the alert will trigger about potential maintenance problem to perform the executable maintenance task. In the case of maintenance task completion, the corresponding item of alert N_{item} is set to normal. In the case of the qualified maintenance operator task whereas the problem cannot be solved by the executable maintenance task, the maintenance operator will be tasked for the maintenance task, and the related item of the alert N_{item} is then 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 is facilitated by different machine-learning techniques to create predictive models of the component asset. Future event prediction about failures is made using the predictive models which utilize available variables and conditions of the past events such as failures. The predictive model is operated by feeding new data and then the results are produced. Predictive Analytics is facilitated by different machine learning methods, data mining and statistics which utilize historical and current data to produce predictive models i.e. predicting future events.

Interoperability is essential for flexible and modular system. In this aspect, the various maintenance items of the manufacturing system can be easily integrated with different processing components [10, 27, 61]. Typically, traditional maintenance approach is manual, and the machine equipment life estimation is usually based on domain experience i.e. whether a maintenance is required or is waited for a failure event of the component is determined by maintenance experts [38]. This is expensive and tends to lead to a downtime in production. In the context of predicting the current equipment useful life, the remaining effective working time is predicted by combining its current state and historical information [38, 62]. Thus, predictive methods can offer prediction accuracy for maintenance activities.

- Typically, four phases of the processing cycle are carried out:
- Identifying phase: Identify use case scenario
- Modeling phase: Learn and train model from data
- Predicting phase: Deploy the model to predict future outcome
- 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 Decision Trees, Regression Analysis or Neural Networks to arrive at conclusions [6, 24, 33, 34, 38, 44, 48, 53, 58, 62]. For instance, in the context of classification and regression analysis using SVM, a supervised learning method [6], each sample is a record that belongs to the unit of time for an asset for the binary classification whereas the regression task is to search for a model that calculates the remaining useful life of each new sample as a continuous number [62]. Generally, the model i.e. predictive is developed by training various data including the historical data of machine condition (health) indicators or equipment condition such as worn, fault, etc. [6, 62].

With advanced technologies such as big data and cloud computing, neural networks have been widely used in machine learning models [19, 33, 34, 62]. Neural network is optimized for identifying patterns and interactions between features, and subsequently producing a best-fit model without a need for predefining features in the model [19]. 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. [19]. The accuracy of trained models will determine the model to be deployed in production [24, 44, 53] 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

Modern collaborative manufacturing industry is complex and dynamic, thus necessitates a concrete flexible architecture platform. In the case of Industry 4.0, the understanding of the industry operations, partners, communication and the underlying technologies is essential to designing predictive maintenance applying the RAMI 4.0 and FIWARE framework. The complex interactions of industry partners and systems involve a variety of different range of applications and systems requiring different interaction schemes and mechanisms. Different approaches for predictive maintenance have been explored in [5, 11, 22, 25, 31, 41, 57, 59]. The most recent approaches such as [5, 31] recognized the aspect of RAMI 4.0 and Industry 4.0, and however they failed to address critical factors such as flexibility, modularity, interoperability and transparency which are essential to developing flexible Industry 4.0 predictive platform. The complexity of the industry in our approach 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 via a high-level view.

The instantiation of FIWARE components further delivers a consistent and flexible manufacturing platform, enabling the integration and interoperability of the predictive maintenance platform with other different 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. In this way, our solution supports the essential features such as flexibility, interoperability of predictive maintenance platform, compared to existing approaches such as [5, 31] which lack the consideration of such features. However, it should be noted that 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 lead to better management of key manufacturing machine equipment and optimization of the whole manufacturing chain.

In a complex and competitive manufacturing industry, transparency and traceability is essential to the whole production collaboration chain. The collaboration aspect of predictive maintenance is mostly ignored by existing approaches [5, 11, 22, 25, 31, 41, 57, 59]. Thus, implementing the IDS connector as well as blockchain storage for data sharing on the proposed solution platform increases transparent collaboration, offering a potential industrial solution. Adopting the proposed Use Case Data Constraints Driven approach described in Section 4.4, 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 potential monetarization. However, data privacy and protection such as GDPR must be critically examined for any implementation.

7. CONCLUSION AND FUTURE WORK

In the context of complex, dynamic and collaborative Industry 4.0 manufacturing, flexible and consistent architecture platform is essential to operate and manage the whole cycle of the production chain effectively. 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 initially focus on the design and instantiation of RAMI 4.0 and FIWARE framework. For future work, the implementation and evaluation of the design platform solution will be performed. This includes additional work on the proposed Use Case Data Constraints Driven approach, predictive models and real-time processing with the presented application case as well as additional use cases across industries.

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