Applying Predictive Maintenance in Flexible Manufacturing

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Abstract. In Industry 4.0 context, manufacturing related processes e.g. design processes, maintenance processes are collaboratively processed across different factories and enterprises. The state i.e. operation, failures of production equipment tools could easily impact on the collaboration and related processes. This complex collaboration requires a flexible and extensible system architecture and platform, to support dynamic collaborations with advanced capabilities such as big data analytics for maintenance. As such, this paper looks at how to support data-driven and flexible predictive maintenance in collaboration using FIWARE? Especially, applying big data analytics and data-driven approach for effective maintenance schedule plan, employing FIWARE Framework, which leads to support collaboration among different organizations modularizing of different related functions and security requirements.

Keywords: Collaboration, Predictive Maintenance, Maintenance Schedule Plan, Industry 4.0.

1 Introduction

Modern collaborative manufacturing industries are advancing to embrace the concept of Industry 4.0 in achieving high levels of productivity and flexibility. Modular collaboration is essential to enabling the flexibility (pluggable components i.e. processes, machine, devices) for cross-organization to work seamlessly [1]. In this aspect, organizations can establish collaboration by connecting devices with required data to perform business functions, enabling the maximum capacity of establishing instant collaboration among collaborative partners [1]. This however requires the underlying system flexible enough to support the collaborative business process whilst maintaining trust and transparency among partners [2]. Besides, the capability of predictive maintenance with a flexible platform is critically important for supporting the whole production chain in the collaborative manufacturing environment.

In Industry 4.0 manufacturing context, the interaction and data exchange occur in various components e.g. systems, machines, IoT, etc., and this facilitates the underlying business processes across different collaborative domains. These collaborative processes produce a huge amount of data and thereby bring opportunities such as big data driven discoveries such as analytics [1, 3]. However, traditional data processing and tools face huge challenges in dealing with big data, advanced analytics and offering a flexible analytics architecture platform [1, 3].

Besides, effective maintenance is critical to the manufacturing chain as it associates with downtime and faulty product which can affect the collaborations i.e. integrated value and processes [4]. Traditional maintenance approaches such as corrective (reactive), preventive, are not effective for the demand of modern collaborative manufacturing due to cost and management concerns [5]. Big data analytics with advanced techniques like machine learning offer an opportunity to maximize maintenance capability, namely predictive maintenance [2]. A flexible predictive maintenance solution is needed to provide effective maintenance management, enhancing the whole maintenance, and production process and minimizing downtime and cost.

This paper looks at how to support flexible predictive maintenance platform complying Industry 4.0 standards and Reference Architecture Model Industry (RAMI) 4.0 using FIWARE framework, which leads to support collaboration among different organizations modularizing of related functions. We look at how to support predictive maintenance for flexible manufacturing, which means we are not only looking at how to maintain one machine with different components but a series of machines within a product line. The contributions of this work are: a) to investigate a predictive maintenance method for supporting multi-machines within a product line, b) to introduce a predictive maintenance method and schedule plan utilizing state-of-the-art approach for supporting flexible manufacturing, and c) using the designed predictive maintenance method to apply to an application case.

2 Related work

Modern industrial collaborative computing is driven by Industry 4.0 [1]. Industry 4.0 can be realized as a collaborative value-creating network that supports flexibility and application of intelligent machines and processes using advanced technologies such as the internet of things (IoT), Cyber Physical Systems (CPS), big data analytics and cloud [1]. In the case of Industry 4.0 manufacturing, business processes are collaboratively processed across different factories and organizations for effective handling of production life cycle and demands [1, 6]. This process however is complex and hence entails a modular platform with flexibility and transparency for the data to flow across different collaborative domains [2].

A flexible and modular architecture platform is essential to supporting modern collaborative industry smart systems [4]. RAMI 4.0 simplifies Industry 4.0 with a three-dimensional model; hierarchy levels, functional layers and product lifecycle value stream [2]. RAMI 4.0 offers a simplified coherent view which provides an understanding of complex systems and processes involved in complex Industry 4.0 [2]. FIWARE, an open source framework exists as a service ecosystem composed of different key components called Generic Enablers (GEs). Using these GE components such as IoT/smart devices, services and big data analysis components, smart solutions can be developed for different needs or processes, promoting interoperability and modularity [4, 7]. Our previous work offers FIWARE predictive maintenance however does not cover the aspect of RAMI 4.0 and maintenance schedule plan [4]. Besides, a 5-level CPS architecture is proposed by [8] to support a step by step approach for designing smart manufacturing systems. This approach is based on a sequential manner which can be difficult to deal with the dynamic changes and demands of modern industry.

2.1 Predictive Maintenance Model

Maintenance is becoming essential to modern manufacturing as it impacts on costs which are related with downtime and faulty products [9]. Predictive maintenance is based on data-driven methods and maintenance activity is scheduled in advance and acted before a failure event occurs [9]. Thus, it offers advanced analytics and a cost-effective option [2, 9], compared with traditional approaches such as corrective, preventive maintenance which are costly and complex [5].

Tool condition detection and Remaining Useful Life (RUL) estimation help to manage optimal predictive maintenance [2, 5]. This facilitates producing effective maintenance schedule plan in advance, subsequently minimizing downtime, cost, and unnecessary maintenance, and maintaining effective operating conditions of machine equipment [2, 9]. RUL estimation of a component derives from the present time and the end of its useful life whereas the degradation or health of a component is considered for the tool condition detection [2, 5].

Time series or sequential sensor data such as operational and condition data collected from manufacturing machine/equipment are used for data-driven predictive models such as tool condition detection aspects, RUL [4]. In this process, Long Short-Term Memory Network (LSTM) well suits for the predictive models [4], compared with other widely used techniques such as sequence learning Hidden Markov Model, Recurrent Neural Network which face different challenges such as computational complexity and storage [10, 11].

In the context of collaborative manufacturing, maintenance is complex as it associates with different systems/components e.g. IoT devices, CNC machines, tools, etc. At this stage, different aspects of maintenance such as single-component and limited multi-component systems are predominantly explored in the research community. In the case of conventional maintenance, single-component systems were focused in [12, 13]. These works generally consider for individual equipment or component and ignore other associated components. Subsequently, multi-component systems become the focus of various works [14–16]. In this context, production equipment with a multi-component system was focused. Moreover, additional considerations such as economic (cost related to machine, fixing, downtime), a dynamic group in maintenance are realized by [15] for cost savings.

At this stage, current approaches still lack the attention for Industry 4.0, particularly considering the nature and increasing application of complex systems i.e. multiple machines with multiple components. Traditional maintenance approaches such as corrective, preventive are ineffective, expensive and possibly initiate human error [9]. Our previous works only focus on the aspect of FIWARE [4] but do not consider for schedule plan and RAMI 4.0 architecture [2]. Thus, this demands a new approach which considers complex systems for optimal maintenance schedule plan in flexible predictive maintenance. In addition to complex systems, key factors such as maintenance task, cost, availability, should be considered in deciding optimal maintenance schedule plan.

3 Predictive Maintenance Model for Flexible Manufacturing

We propose the predictive maintenance model described in Fig. 1, which supports the proposed predictive maintenance for flexible manufacturing. The predictive maintenance module takes as inputs of data from machines as well as data related to machines and generates the outcomes of the predictive models that forecast the future machine conditions assisting decision making for optimal maintenance schedule plan.

There are three main functions in the predictive maintenance model, namely data collection, data processing, and maintenance analysis. The **data collection** in general is online activities related to various data. First data needs to be collected from different machines within a product line of flexible manufacturing; online data collection allows data to be received synchronously from the product line. Secondly, real-time data can better reflect the machines' conditions. In a flexible manufacturing environment, various data such as operation, event and condition data are collected [2]; operation data refers to data about the certain process; event data generally refers to information about what happened to the asset i.e. machine equipment, and which maintenance was applied to it; condition data such as health and measurements of the physical asset. Moreover, various sensors such as ultrasonic sensors, accelerometers, gyroscopes, etc. are used for dealing with different data signals such as vibrations, pressure, temperature, etc. exist and [17]. Various data storages such as relational database, NoSQL, Hadoop or data lake can be used for different needs i.e. streaming, structured data etc. [3].

The **data processing** concerns with the general operations conducted to producing insight from a large amount of data [18]. Raw data must be converted into information for decision making [18]. Typically, data preprocessing, cleaning and reduction, are carried out [3]. *Data preprocessing* may involve removing redundant or inconsistent data whereas *data cleaning* might deal with missing value, format. *Data reduction* generally deals with transforming data into ordered, meaningful, and simplified forms such as feature or case collection [3]. In the proposed model, data processing also concerns with both online and offline. The online aspect refers to real-time monitoring and alert notification. For this process, the condition and status of the machine equipment or tool of the production system are considered. Typically, the real-time data about status or condition is compared with the threshold of the machine equipment maintained in a database for monitoring and notification.

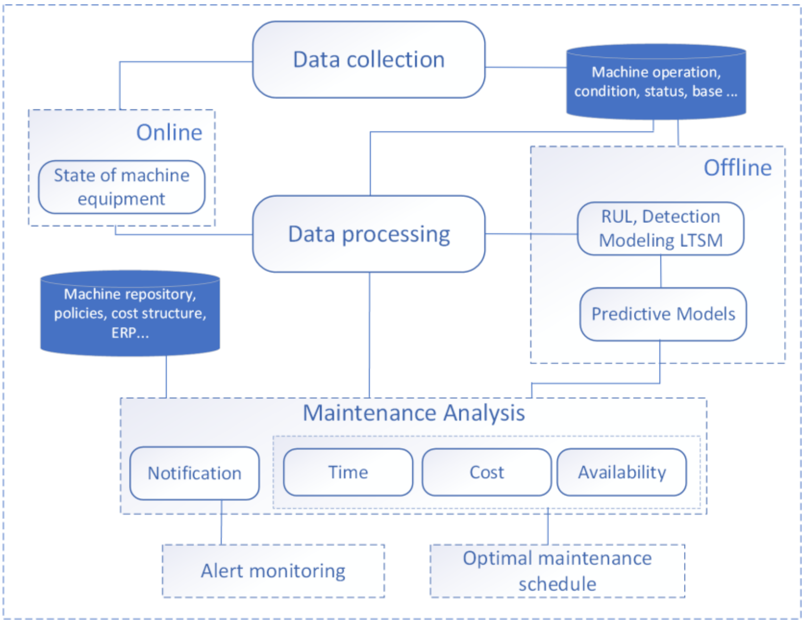

Fig. 1. Proposed Predictive Maintenance Model

Regarding the offline aspect, it focuses on the predictive models such as RUL and detection of machine tool wear, derived from LSTM. The trained models are deployed and used for RUL estimation and detection for potential problems arising in production. To facilitate capabilities such as big data analytics of predictive maintenance, various data such as sensors, manufacturer data and machine tool operator data are utilized for predicting the machine condition and RUL [4, 5]. Regarding the machine conditions and RUL, the machine components of the same type with failure data or any event that states the end of the component life [2].

As for the real-time aspect i.e. alert, monitoring in the dashboard, the underlying assets i.e. machine, device, factory, etc. are considered [2]. For online processing in Algorithm 1, real-time operational data derived from the underlying machine/equipment N is processed and compared with the threshold. When the state i is above the threshold i, the alert i will prompt to perform the executable maintenance task for the qualified item j. In this case, maintenance task such as minor adjustment which can be executed by automation, is considered. If the maintenance task cannot solve the problem, the qualified available maintenance operator k will be required, and the corresponding item of alert i will then also be set to normal. In this case, a database with the maintenance repository is used for storing the key threshold of the asset i.e. machine equipment.

At the **maintenance analysis,** it takes as inputs the outcomes of the predictive models that forecast the future machine conditions assisting decision making for optimal maintenance schedule plan. The result of maintenance analysis both online and offline will be presented in a dashboard. Different notification and the maintenance analysis based on time, cost, and availability are involved in this level. Based on the notification of machine condition of each asset (including its future trend) and RUL, the Maintenance Analysis module provides the probability necessary for computing the weights following Algorithm 2 and 3.

```
Algorithm 1: Online (Real-time) processing
    for each maintenance asset i to N do
         if state(i) < threshold(i) then break end if // exit as not outstanding asset
         set alert(i) = true
         for each maintenance task j of item(i) do
             if task(j) == true then
                do maintenance task (j) // automation maintenance
                waitForTaskExecution()
                if(state(i) < threshold (i)) then
                     set alert(i) = false // set as completed
                else
                for k of operator(i) do
                   if operator (k) == true then
                      do maintenance task (j)
                      set maintenance task (j) = false
                      set alert(i) = false
                   end if
                end for
              end if
              if (alert(i) == false) then break end if
         end for
     end for

Algorithm 2: Maintenance schedule processing
     Output maintenance schedule plan
     Initialize maintenance schedule = null
     Set cost = 0, time = 0, availability = 0
     maintenanceAssets = Get Maintenance Assets // invoke algorithm 3
     // compute for each maintenance assets
     availability = Compute Maintenance Availability (maintenanceAssets)
     time = Compute Maintenance Time (maintenanceAssets)
     cost = Compute Maintenance Cost (maintenanceAssets)
     // get the optimal schedule by overall minimum cost
     maintenance schedule = min (cost, time, availability)
     return maintenance schedule

Algorithm 3: Get maintenance assets (multi-machines/components) processing
     Output maintenance assets
     Initialize maintenance_assets = null
     maintenanceAssets = Get Machine Assets // from database for outstanding alerts
     for each m in maintenanceAssets do
          if m is multiple machine or component then
              for each k in m do
                  if k requires maintenance then
                     maintenance_assets += k
                  else
                     break
                  end if
              end for
           else m is single machine or component then
              if m requires maintenance then
                  maintenance_assets += m
              else break end if
           end if
      end for
      return maintenance_assets
```

The Maintenance Analysis module determines the maintenance schedule plan for all the activities that can be computed as the estimated automation task or operator/engineer displacement time from the assets (machine equipment). This also depends on the relative positions of the assets, the displacement time or automation of the repair machine equipment of the completed maintenance activity. The cost associated with the operation, downtimes, repair, etc. to the asset *m*. Note that, all these costs depend also on the characteristics of the task and operator. The availability is associated with the asset items for maintenance (e.g. work in progress production).

The schedule activity is triggered via the Optimal Maintenance Scheduling module, which determines the optimal maintenance schedule by considering the above-determined maintenance constraints such as cost, time, and availability. Subsequently effective maintenance schedule plan can be produced, enabling optimal procedure task.

4 Predictive Maintenance Model Application Case

A flexible manufacturing factory operates with a variety of systems such as processing, logistics, information, machine equipment tools, collaborative processes and data, etc. Fig. 2 depicts an example of the flexible factory. In this case, the processing system operates with three robots, 4 sets of machines, AGV trolleys, carrier plates and a warehouse. For operation such as measurement, cleaning and drying the workpiece, machine tools such as coordinate measuring machine, cleaning machine, drying machine are utilized. During operation, these different machines equipment tools generate various data. Besides, collaborative processes or data are processed or accessed across collaborative domains i.e. suppliers, machine manufacturers, insurers, etc.

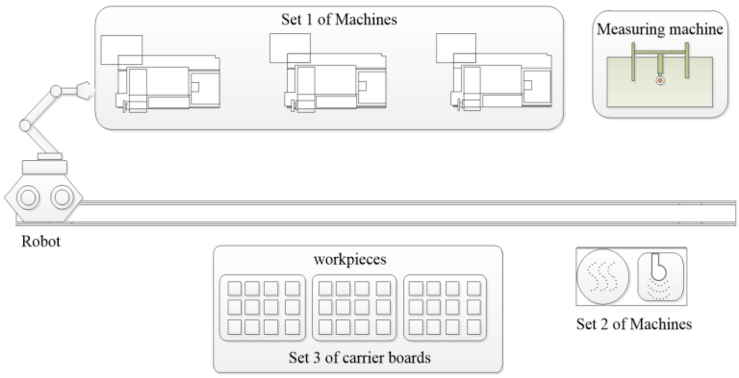

Fig. 2. Flexible Manufacturing Factory

From our literature review in Section 2, it is realized that FIWARE framework with RAMI 4.0 offers the flexibility, modularity and simplified architecture which are critical to the application case to effectively manage dynamic collaborations, productivity, product life cycle and costs. To achieve an optimal solution and satisfy the standards of Industry 4.0, FIWARE framework in the context of RAMI 4.0 and data model from [4] are thus adopted for the proposed predictive maintenance. The proposed predictive maintenance model in Fig. 1 is applied for the application case applying RAMI 4.0 and key components of FIWARE framework in Fig. 3.

At the resource module, the assets i.e. factory machines, robots, etc. represent the asset layer of RAMI 4.0, operate and connect with the Orion context broker, associated processes and data storage via related adapters. In the middleware and data module, it represents the communication and information layer of RAMI 4.0 and using NGSI REST API and PEP Proxy for interaction and security enforcement, the Orion context broker facilitates the context data processing to the process module and data storage such as HDFS as the data layer. At the process module, it represents the functional layer of RAMI 4.0 and Cosmos Big Data analysis enables both batch and stream processing including Hadoop engine, and related predictive models which are connected to the context broker and the application module [7]. Various applications and user interfaces can be integrated as required at the application module, representing the business layer of RAMI 4.0. Moreover, real-time data triggered by the asset can be served by different applications such as QuantumLeap, Grafana, Hive, etc.

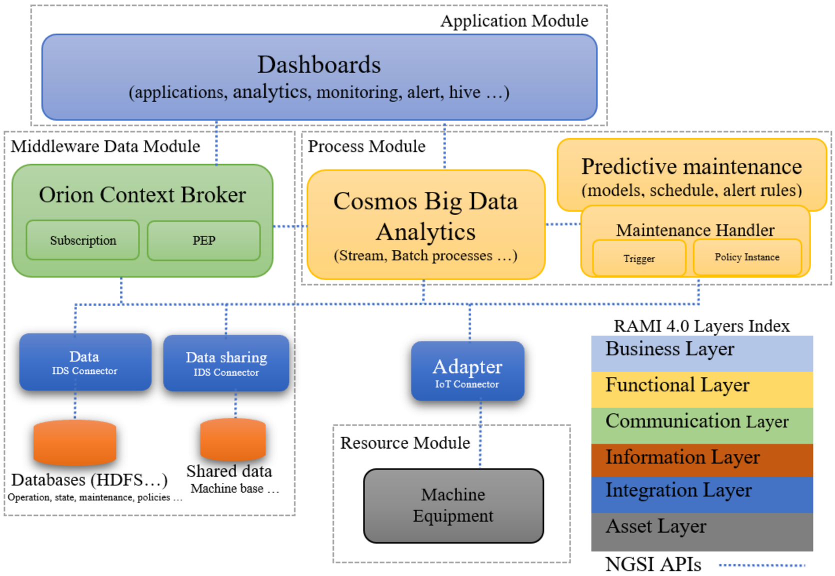

Fig. 3. RAMI 4.0 FIWARE Predictive Maintenance Model for Application Case

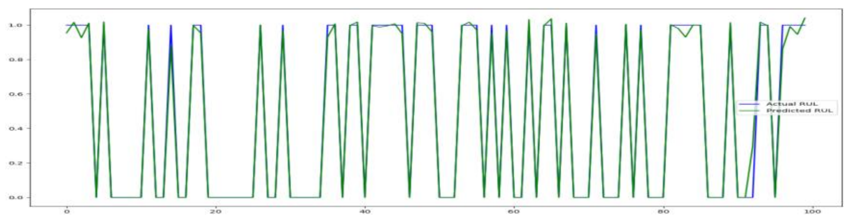

Fig. 4. Initial result from sample flexible manufacturing dataset

An initial result trained from a sample dataset for the predictive model using Keras, TensorFlow backend and the Adam optimizer is presented in Fig. 4. Optimized model learning will be conducted before deployment.

The analysis based on the predictive models such as RUL, detection and maintenance analysis information related to maintenance cost, time and availability from the machine repository (machine schedule, availability, design, capabilities, configurations, parameters, etc.) stored in a database using the adopted data model from [4], are available via the dashboards. As a result, the maintenance operators can obtain information about the availability of the resources towards the creation of effective maintenance schedule process plans via the dashboard. Subsequently it will reduce downtimes, cost and enhance the production chain.

A network of collaborations in different processes such as machines, suppliers, machine manufacturers, insurers, customers exists in the case, and this poses challenges such as trust among collaborative partners. To support transparent collaboration, FIWARE's IDS connectors are utilized for accessing and processing collaborative data such as machine base data from manufacturers, machine diagnosis for insurers, and product design data from designers. This facilitates transparent interaction and data exchange across collaborations enabling access usage policy and thus traceability. FIWARE container virtualization is adopted for better scalability of the proposed solution.

5 Conclusion

Modern collaborative manufacturing is complex, face different challenges, and requires a flexible architecture platform that will assist in managing optimal maintenance. We proposed a Predictive Maintenance Model that offers a flexible and modular system using FIWARE and RAMI 4.0 complying Industry 4.0 standards and enabling advanced analytics such as LSTM models. Using a flexible manufacturing case, the proposed model is demonstrated in a way that different systems or processes can be integrated in a modular fashion, and effective maintenance schedule can be planned. Ultimately, it enables effective maintenance management, enhancing the whole production and maintenance process with transparent collaboration, and minimizing downtime and cost. Lastly, optimized predictive and maintenance schedule models with both application case and other use cases across the industry will be performed and evaluated in future work.

Acknowledgments. This research is partially funded by the State Key Research and Development Program of China (2017YFE0118700) and it is part of the FIRST project which has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 734599.

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