Predictive Maintenance for Industry 4.0

A holistic approach to performing predictive maintenance as a service

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Copyright Statement

Abstract

In modern collaborative industry, the machine equipment involved has rapidly increased. Many of the involved machines are complex and can only work in good maintenance conditions. Any failure of this equipment and related tools can easily lead to unintended disruption. Due to the collaborative nature of the manufacturing systems, one machine failure could result in undesired downtimes beyond single production lines and add costs to the value-added processes of the partner enterprises in the entire value chain.

Industry 4.0 provides a concept of the interoperation of data, processes, and services within one enterprise as well as interoperation among different partner organizations. This increases dependencies and potential for failure related costs. There is, however, a lack of work that focusses on predictive maintenance services in the context of Industry 4.0 supported architecture and standards.

This thesis looks at how data-driven predictive maintenance under existing Industry 4.0 concepts, architecture, and platforms can be supported. A flexible predictive maintenance case is used to design the predictive maintenance modules that fit within the industry standard Reference Architectural Model Industrie 4.0 (RAMI 4.0) model. Beyond looking at predictive maintenance for a specific manufacturing type, the research further looks at predictive maintenance as a service as well as forming a virtual factory specialized in supporting predictive maintenance.

Adopting the design science research methodology, the dissertation designs Industry 4.0 Predictive Maintenance Architecture, algorithms of predictive maintenance modules for estimating RUL (Remaining Useful Life) and maintenance scheduling modules for supporting multiple machines/components. The design of architecture and algorithms are implemented within the leading FIWARE platform.

The results are verified in terms of performance. The modular predictive model achieves higher accuracy and lower RMSE score at over 19% than comparator methods. The predictive maintenance service enabled by designed algorithms of predictive model and maintenance service scheduling can offer over 30% for optimal cost and 10% for downtime impact to the manufacturing network.

Dedication

To my *Mum, Reg, Jenny*, and *everyone* who has helped me . . .

Declaration

This thesis is the result of my own work. The pronouns *we* and *our* in the text have been used for stylistic reasons.

Acknowledgements

I give thanks and praise to God for the amazing blessings, faithfulness, and grace. Thank you, Jesus. *Psalms 121*

I would like to express my profound gratitude to my first supervisor Dr. Lai Xu for the professional guidance, academic advice, and encouragement. Thank you for all your help, Lai. Great appreciation to Dr. Paul de Vrieze for the continuous guidance and help. Thank you, Paul. Thanks to Prof. Hongnian Yu as my third supervisor.

To my Mum, brothers and sisters, my uncle, families, to Reg, Jenny, and friends in Bournemouth for their love, support, and prayers.

Table of contents

List of figures

List of tables

List of Algorithms

Chapter 1

Introduction

Manufacturing utilizes complex and expensive machine equipment tools for running factory operation. Over time, these machines wear out and get misaligned. The worn/misaligned machines have reduced lifespans as well as are generally less efficient and thus may result in potential reduced product quality. Unplanned downtime and damage caused by reduced maintenance is ideally avoided. Downtime and maintenance may also be triggered by the excessive or unnecessary maintenance caused by machines' failure (Mobley, 2002). Conventional maintenance is costly. This leads to a need for predictive maintenance.

Predictive maintenance is based on predictive models derived from data including operation and condition of industrial assets i.e. machine equipment tools, that assists in the prediction of potential failure or breakdown of the industrial assets (Mobley, 2002). It facilitates maintenance analysis by offering a prognosis of faults in related different machinery and deficient processes using predictions and various analyses. Predictive maintenance involves two key components: Inquisition of knowledge through analytics i.e. prediction and detection of machine tools, assisting in schedule planning and maintenance decision making for the required maintenance task to be completed. Figure 1.1 shows the different approaches that maintenance can be performed. The conventional approaches rely on expert knowledge, actual system degradation models and may be designed to wait until failures occur, something that may be costly and untimely. Unlike the conventional approaches, predictive approaches focus on a data-driven approach utilizing various data generated from factory machine equipment tools and operation, and other information processing systems. The application of data-driven predictive maintenance approaches in manufacturing industries can reduce maintenance costs up to 30% and eliminate breakdowns up to 75% in comparison to conventional preventive maintenance (Gao et al., 2015).

Industry 4.0 collaboratively streamlines the manufacturing related processes for greater flexibility and productivity (Zezulka et al., 2016). It enables flexible collaboration as plug-

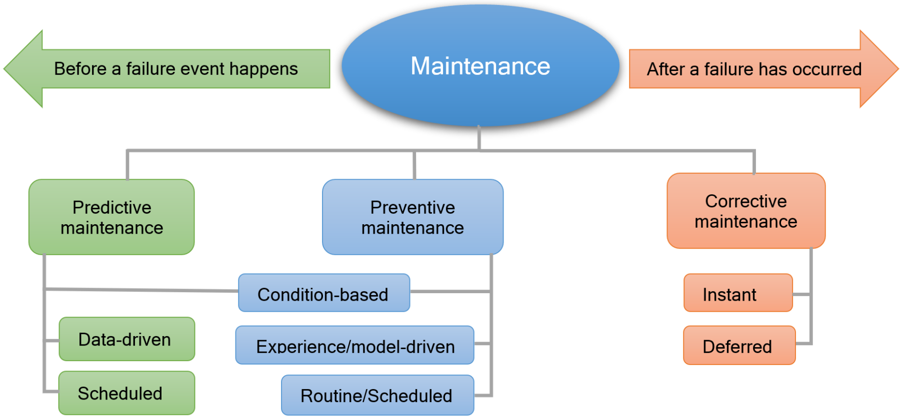


Fig. 1.1 An Overview of Maintenance Strategy

gable components, processes, machine devices which facilitates diverse enterprises to work seamlessly across boundary. Different enterprises can move related business processes beyond its boundary including machines/devices/processes assisted by advanced technologies. In this context, industrial systems are complex due, in part, to collaborative growing size, and to the integration of new technologies. Different machines, components and equipment tools are connected via sensor devices collecting operation/condition data, as well as are configured specifically for a product line. This brings complexity in collaboration of systems, connected machine devices and related processes such as predictive maintenance (i.e. managing predictive maintenance become challenging as the number of product line and the different types and number of machine equipment tools increase).

Over time, the condition of the complex factory machines *(particularly the complexity makes this more of a challenge for Industry 4.0 machines)* is hampered by the usage and age. This eventually leads to deficient operation or a machine failure if no maintenance action is taken. Predictive maintenance activities regarding complex systems are hard and expensive. Ultimately the failures of the machine equipment tools may result in undesired downtime and costs. The impact is accounted for an estimation of $50 billion per year for the global industry by unplanned downtimes (Deloitte, n.d.).

As Industry 4.0 involves multiple business partners operating in a complex and collaborative manufacturing, the complexity of the collaborative system/process as well as the challenges for data collation and collection increases. In manufacturing Industry 4.0, diverse systems are interacted by exchanging data at various levels i.e. machines, IoT, devices, etc. These processes subsequently generate voluminous data and thereby offer opportunities for reliable prediction that can be used for predictive maintenance. This however requires a concrete flexible platform which supports modularity, interoperability, and advanced capability of big data analytics for collaborative Industry 4.0 manufacturing (Thoben et al., 2017; Zezulka et al., 2016).

In this research study, the research questions (i.e., Section 1.2) are formed based on the challenges in the field of predictive maintenance in Industry 4.0. By answering the questions, major contributions are made.

Current research in predictive maintenance is mainly focused on a single shopfloor or factory. Recent works have started using service oriented architecture (and components such as Enterprise Service Bus – ESB). From an architectural perspective, a common basis is RAMI 4.0.

In contrast to the other work, this research takes a broader, more generic, approach with an architecture, predictive model and maintenance schedule services that could be applied by various organizations or factories. The approach complies with Industry 4.0 concepts and standards. The proposed methods are designed to work together and be able to be used as predictive maintenance as a service. In this approach, multiple distinct organizations can consume the predictive maintenance services using framework adapters to connect their own data.

To support modular predictive maintenance of a service, predictive models are stored in, and can be used from, a model repository. These predictive models (i.e., deep learning models), can be parameterized to work with data from various machines or devices. To aid users in selecting appropriate models, the repository provides selection criteria for the models.

Based upon the predictive models, predictive maintenance as a service can schedule maintenance. This scheduling is performed considering various situations, i.e., multiple, potentially independent, factories (collaborative manufacturing networks), multiple production lines in a factory, multiple machines in a production line, multiple components per machine etc. The proposed design and implementation can adapt to and be justified for the diverse needs of real-world manufacturing.

Overall, the proposed predictive maintenance approach is designed in line with the Industry 4.0 framework. Prediction of maintenance needs is done using machine learning approaches that can be adjusted for different data sets and pre-trained predictive models can be initially provided to support unfamiliar users. The resulting predictive maintenance scheduling methods can take into account various factors and optimization goals in the planning decisions.

1.1 Challenges in the field of predictive maintenance

As the manufacturing operation and its machine equipment tools become increasing complex, and are connected with many different machines/components as well as manufacturing partners' systems, the complexity of maintenance i.e. managing and planning maintenance activity of multiple machines/components, is drastically increasing (Zezulka et al., 2016). The field of predictive maintenance has several challenges that should be addressed. These challenges include: in the context of complex machine equipment tools, existing predictive maintenance processes are inefficient; challenges in the management of the information required for predictive maintenance activities; reliance on traditional maintenance approaches such as routine/regular activity based on domain expert; increasingly complex and collaborative manufacturing networks responding increasingly dynamic demand reduce the predictability of maintenance needs.

In the context of complex machine equipment tools, existing predictive maintenance processes are inefficient: for example in a production line, CNC machines are utilized with different sets of machines/components including robots as shown in Figure 1.2. All these different machine equipment tools are connected and operated based on production needs/settings. The machines/components of CNC are routinely inspected by factory engineers, and maintenance tasks such as repair or replacement is carried out appropriately. Normally the CNC machine is not in a good condition is known by the defects of the artefacts (the result components of the product line). According to domain experts, the maintenance process is happening to different machines/components based on which machines/components operate most frequently for specific production. A machine may not be required for a particular factory operation based on the production of a certain product, and different settings may then be required for adjusting the factory operation. This leads to more complex management of predictive maintenance as additional routine inspections are required for the verification of maintenance required for different machines/components and associated maintenance spares, or tools.

Challenges in the management of the information required for predictive maintenance activities: during operation, unexpected events such as one component or machine breaks down, may happen, then the component/machine needs to be checked and then repaired or replaced by the factory engineers even if the production run is not completed (Mobley, 2002). This is an expensive process because every time a machine/component is repaired or replaced, the whole production line must be shut down, the machine/component is taken out of the factory floor and repaired or replaced. If the inspection is reasonably short (i.e., known failure, etc.), then the production line is resumed at a reasonable time. Otherwise, the production line is shut down, possibly 6 hours to replace the failed machine/component including shutdown,

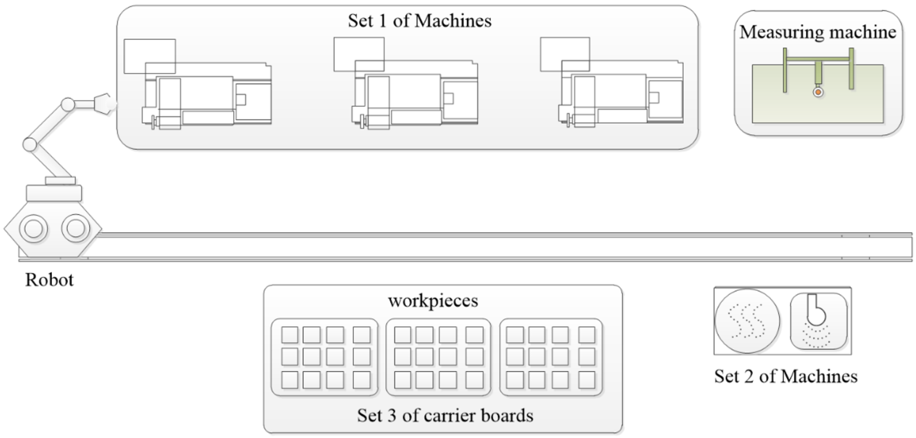


Fig. 1.2 A factory product line layout of FIRST Flexible Manufacturing (Sang, Xu, de Vrieze and Bai, 2020*a*)

re-start, testing, etc. Subsequently, the overall maintenance cost is increasingly added by the delay or downtime cost to the manufacturing chain. Thus, it is valuable to investigate potential ways to predict the operation condition of the machines/components.

Reliance on traditional maintenance approaches such as routine/regular activity based on domain expert: although sensors and data loggers are currently installed in the process and different data storage servers are available for the case in Figure 1.2, the maintenance decisions are still made based on experience i.e., domain experts or factory engineers assisted by Manufacturing Execution System (MES). From process point of view, the engineers and the management teams have a brief picture (different prospective) of what may be the reason of the machine equipment tools, however none of those reasons are confirmed or validated, as any inspection of events such as breakdown or failure, etc., is usually difficult due to the complex nature of the different complex machines/components including the employment of robots, CNC machines and their settings, operating in the production line.

Increasingly complex and collaborative manufacturing networks responding increasingly dynamic demand reduce the predictability of maintenance needs: due to requirements such as increasing product variety, dynamic/varying demands, product short life cycle, and shorter time to market, the modern industrial cases such as the FIRST are required to operate factory operation more efficiently, e.g., to integrate various systems such as cyber physical systems, robots, CNCs, etc., as well as to work beyond its boundary, requiring the integration of process/system from business partners e.g., machine manufacturers, suppliers, designers (Zezulka et al., 2016). This demands the industries to act quickly and respond to the required demands.

In general, the operations in Industry 4.0 manufacturing are facilitated by advanced technologies such as cyber physical systems, smart machines, etc. that are collaboratively linked (Thoben et al., 2017; Zezulka et al., 2016). In this context, the interactions among the different systems generate big data, from both the collective systems' processes and the related environment where the processes are being executed. Smart machines and machines that are networked can support better prediction of potential issue i.e. worn/failure/breakdown of the individual machines or related components. For making the decision on when to do maintenance in which cost under different constraints (e.g. availability of engineers, hardware), factory information and related business processes are utilized for optimized results with satisfying multiple criteria.

As Industry 4.0 is increasingly adopted, the complexity of machine equipment tools involved in the collaborative industry has rapidly increased (Koren et al., 2018; Thoben et al., 2017; Zezulka et al., 2016). As such, predictive maintenance should consider the dependencies of various machine components involved. Thus, a concrete strategy that can efficiently coordinates the failure prediction and maintenance schedule, to ensure optimized operation and productivity, is critically important.

For designing and implementation of predictive maintenance, first, the collection of data from different multiple sources for producing information is required. Different domains/sources produce various data i.e., big data with different forms; hence it must be managed properly. Second, new methods and advanced technologies supporting big data analytics are needed since traditional data processing methods and tools are unable to process big data and related processes such as predictive models. Third, Industry 4.0 manufacturing involves complex systems, processes and thus is complex. Traditional maintenance cannot meet the demands of complex systems in providing an effective maintenance decision making (Mobley, 2002).

1.2 Research Questions

Based upon the challenges described above, it is clear that there is an opportunity for an Industry 4.0 based, data-driven predictive maintenance approach. In this thesis we will present such an approach that provides a flexible predictive maintenance architecture platform, complying with Industry 4.0 standards that allows the flexible integration of different machine equipment tools, and factory data sources for maintenance analytics i.e. predictive maintenance model and maintenance decision making that utilize data-driven and state-of-the-art methods such as deep learning.

Thus, this research will:

- investigate a way of constructing flexible predictive maintenance architecture platform, complying with Industry 4.0 standards (considering to integrate business processes and manufacture processes),
- that allows the flexible integration of different machine equipment tools, and factory data sources for maintenance analytics, e.g., the correlation among different parameters and the relation between a combination of parameters and machines/components with limited amount of data samples,
- assisting predictive maintenance schedule plan considering production processes as well as maintenance related operational factors, for factory engineers or operators utilizing advanced capabilities such as big data analytics, deep learning, etc.,
- leading to the facilitation of modular predictive maintenance as a service in the context of Industry 4.0.

To achieve effective collaborative manufacturing in the context of industry 4.0, a new approach is required to provide a flexible platform with maintenance services. This platform should enable dynamic collaboration and advanced capabilities of predictive maintenance. The services provided in the platform align with industry 4.0 standards, architecture, and other related technologies. Therefore, the predictive maintenance needs to be a module/service of Industry 4.0 framework/platform.

Thus, the motivation of this research study is to present a flexible platform for predictive maintenance in Industry 4.0. This will facilitate a modular platform with predictive maintenance considering both prediction as well as schedule plan for multiple machines/components in the context of Industry 4.0.

An ideal research outcome of the Industry 4.0 predictive maintenance model could be given modular integration of different systems/processes/machines etc., complying with Industry 4.0 standards, supporting predictive model for a set of parameter value in a specific time window, the condition of the machines/components can be predicted, and predictive maintenance scheduling can be planned by data-driven i.e., predictive model approach considering multiple machines/components. Such that the factory maintenance engineer or operator will only repair or replace the machine/component when it is necessary, and subsequently downtime and maintenance cost are reduced.

To achieve the motivation of the research study, the primary research question and related sub-questions are formed. To support in formulating the research questions, the related key concepts in the research field are established as depicted in Figure 1.3.

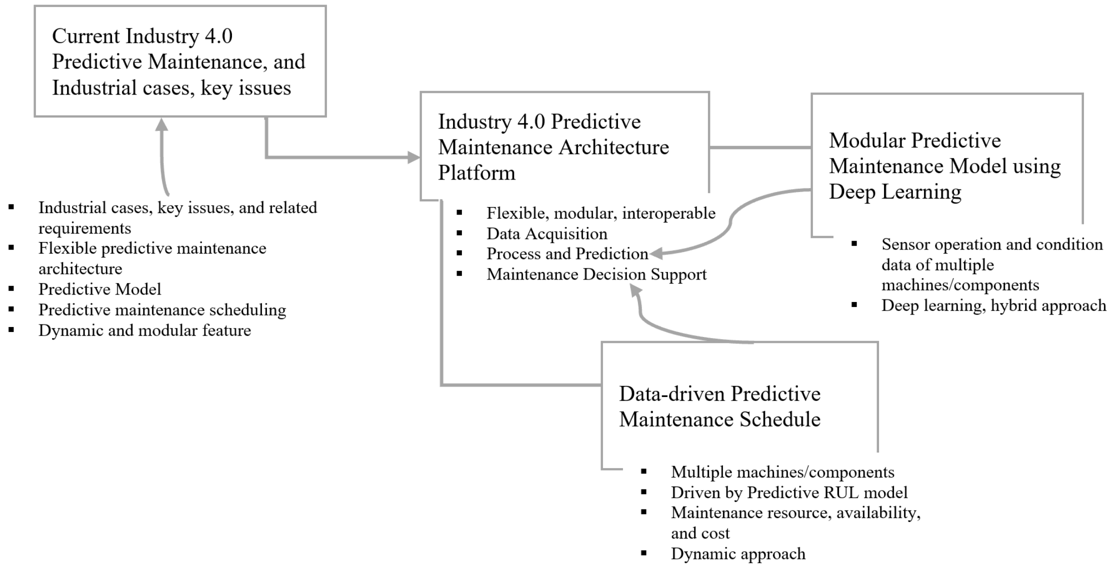


Fig. 1.3 Research Focus

Figure 1.3 illustrates the various concepts of a flexible Industry 4.0 predictive maintenance architecture which facilitates the modular integration of complex systems, diverse data sources, advanced capabilities such as predictive maintenance model, predictive maintenance schedule, enabling better maintenance decision support to reduce downtime and associated maintenance cost.

Primary Question

How can predictive maintenance as a service be provided in an Industry 4.0 context?

Industry 4.0 brings opportunities such as flexibility of collaboration i.e., machines, business processes, as well as advanced capabilities facilitated by the application of big data, deep learning, etc. In this context, several machines, business processes operate together towards a common business goal across factories and enterprises. From the manufacturing aspect, it is required to be proactive in maintaining the factory machines in an optimal way, to avoid downtime and associated maintenance cost. Essentially, a manufacturing could potentially offer the predictive maintenance as a service to the partners' factories in the complex collaborative network.

As such, the research question is formed to investigate in supporting predictive maintenance as a service in an Industry 4.0 context. From the related key concepts of the research field i.e., Industry 4.0 and predictive maintenance in Figure 1.3, supporting Industry 4.0 predictive maintenance requires different key components that are interlinked.

Thus, the following sub-questions of the primary research question are formulated to tackle the research study more effectively.

Sub-question – 1

How can predictive maintenance, and the relevant data collection, be integrated into an overall manufacturing process architecture?

This question relates to Industry 4.0 predictive maintenance architecture in Figure 1.3. Industry 4.0 focusing manufacturing operates with complex and advanced machines, devices and business processes that require high degree of flexibility and advanced capability due to dynamic demands such as short product lifecycle (Zezulka et al., 2016).

Based on the related items such as flexible architecture models in the current industry 4.0 predictive maintenance, industrial cases and key issues as illustrated in Figure 1.3, the research work will investigate how the flexibility in which many different machines/systems/processes can be integrated and operated for required manufacturing process? How the operation of these machines/processes that generates a large amount of data that can be utilized for maintenance analytics?

Sub-question – 2

How can individual machine remaining useful life be predicted based upon relevant considerations? What considerations are relevant for remaining useful life (RUL) determination?

One key function of predictive maintenance is the capability in which the prediction of pending failure of machine equipment tools (Mobley, 2002). Factory machines involved in an advanced manufacturing are of complex systems as well as producing high frequency data such as sensor data which cannot be processed by traditional processing and tools (Shrouf et al., 2014; Zhou et al., 2015; Zonta et al., 2020). What are the key considerations that can assist in developing a predictive maintenance mode for RUL in a dynamic and complex environment such as advanced manufacturing? The work will investigate the related items that will lead to creating a *Modular Predictive Maintenance Model* in Figure 1.3.

Based on the identified considerations, how can a predictive maintenance model for RUL estimation can be developed, supporting the component, *Modular Predictive Maintenance Model* in Figure 1.3? The developed method will lead to operating the predictive maintenance scheduling driven by RUL component in Figure 1.3 that will assist in maintenance decision making.

Sub-question – 3

> *How can predictive maintenance planning be done based upon relevant factors? What factors are relevant for predictive maintenance scheduling?*

In the context of advanced manufacturing, complex systems are utilized for production operation. This increases the complexity that is the degree of maintaining and planning maintenance activity for the multiple machines/systems. Traditional approaches such as reactive or preventive are not effective in dealing with the complexity as well as demands such as dynamic, of complex manufacturing (Zezulka et al., 2016; Zonta et al., 2020).

As such, the question will attempt to investigate the key factors that requires for predictive maintenance scheduling and how can the factors be used in achieving optimal predictive maintenance scheduling? This subsequently will lead to facilitating the development of the component, predictive maintenance scheduling driven by RUL component in Figure 1.3.

Based on the identified factors, how to best support the predictive maintenance scheduling driven by RUL component in Figure 1.3 considering multi-machine, complex manufacturing context?

1.3 Contributions

The answering of the research questions leads to 4 distinct contributions:

- Flexible architecture platform for Industry 4.0 Predictive maintenance
  - A *Predictive Maintenance Model for Industry (PMMI 4.0)* was proposed for supporting the complexity of Industry 4.0 by adopting RAMI 4.0 layered architecture. *PMMI 4.0* facilitates interoperability by complying Industry 4.0 standards

and enabling flexibility by the ease integration of related business functions in a modular fashion.

  - *PMMI 4.0* is presented at Chapter 5 and related journals/papers *Paper 1, 2, 4, Journal 1, 3* were published.

- Modular Predictive Maintenance model

  - A *Modular Predictive Maintenance Model using Hybrid Deep Learning Approach (MPMMHDLA)* was proposed for predictive maintenance RUL model utilizing a hybrid deep learning approach and facilitating the ease construction of model dealing with business needs such as new dataset, model configuration, tuning, in a dynamic manner.
  - *MPMMHDLA* is presented at Chapter 6 and related journals/papers *Paper 2, Journal 1* were published.

- A Data-Driven Predictive Maintenance Scheduling

  - A *Predictive Maintenance Schedule for Industry 4.0 Multiple Machines and Components (PMS4MMC)* was proposed for predictive maintenance scheduling approach based on data-driven, predictive model that assist in dealing with the demands of complex manufacturing settings such as multiple machines/components, for business users such as factory staff, engineer, in their maintenance decision making in an optimal and prescriptive way.
  - *PMS4MMC* is presented at Chapter 7 and related journals/papers *Paper 3, Journal 1, 3* were published.

- An implementation of the solutions as FIWARE enablers

  - The proposed *PMMI 4.0* adopted FIWARE as its implementation platform, complying Industry 4.0 standards and increasing interoperability for flexible industrial implementation. The developed solutions i.e., *MPMMHDLA* and *PMS4MMC* are developed as FIWARE embedded enablers, facilitating modular components for straightforward application by industry, enabling dealing with dynamic business needs.
  - We explain *PMMI 4.0* in Chapter 5, *MPMMHDLA* at Chapter 6, *PMS4MMC* at Chapter 7 and related journals/papers *Paper 2, 3, Journal 1, 3* were published.

Further contributions to the EU H2020 FIRST[1] project deliverable were made as below:

- Industry 4.0 Predictive Maintenance Architecture Platform based on FIWARE And RAMI 4.0
- Implementation Analysis and Application of modular predictive maintenance model using deep learning approach for Industry 4.0 Industrial Flexible Manufacturing Case
- Implementation Analysis and Application of predictive maintenance driven by predictive model and utilization of maintenance scheduling optimization for Industry 4.0 Flexible Manufacturing and Virtual Factory Cases

1.4 Structure

The thesis is divided into following interlinked chapters as Figure 1.4 illustrates:

- *Chapter 2* describes the related work for the research field as a whole, and underpinning for individual contributions.
- Where applicable the discussion and evaluation are performed using the industrial cases as described in *Chapter 3*.
- The research questions are going to be addressed according to the *methodology in Chapter 4*
- Based upon the methodology, case study and related work, *chapter 5* presents and evaluates *Predictive Maintenance Model for Industry 4.0 (PMMI 4.0)* including the concepts, processes relevant to its architecture platform. Using the FIRST industrial case, PMMI 4.0 is verified and its applicability and validation as well as evaluation and comparison analysis are presented; (the contribution(s) in this chapter and RQs)
- *Chapter 6* presents and evaluates *(Modular Predictive Maintenance Model using Hybrid Deep Learning Approach (MPMMHDLA))* which is a hybrid deep learning approach supporting modularity. An industrial dataset from the case study is used to build the model. The results of the evaluation and comparison analysis are provided.

[1] The EU H2020 FIRST project is a competitive consortium with profound knowledge and expertise in complex software systems and manufacturing automation, which aims to support the research and development of virtual factories (First, n.d.). The research bases of Bournemouth, Groningen, Roma, Shanghai, and Modena will be used as a foundation for innovations to contribute to virtual interoperation of smart manufacturing in the area of Factory of the Future/Manufacturing 2.0. The objective of this project being to improve the competitiveness of our industrial partners and sustainability of the European manufacturing sector through establishing a collaborative research network.

- *Chapter 7* presents and evaluates *Predictive Maintenance Schedule for Industry 4.0 Multiple Machines and Components (PMS4MMC)* using the identified key factors in the context of Industry 4.0. It presents the experiment study, its applicability and effectiveness using the industrial cases as well as performance comparisons.
- Finally, *chapter 8* reflects upon the research questions and contributions and discusses limitations and opportunities for future work.

A summary of the chapter outlines is provided in Figure 1.4.

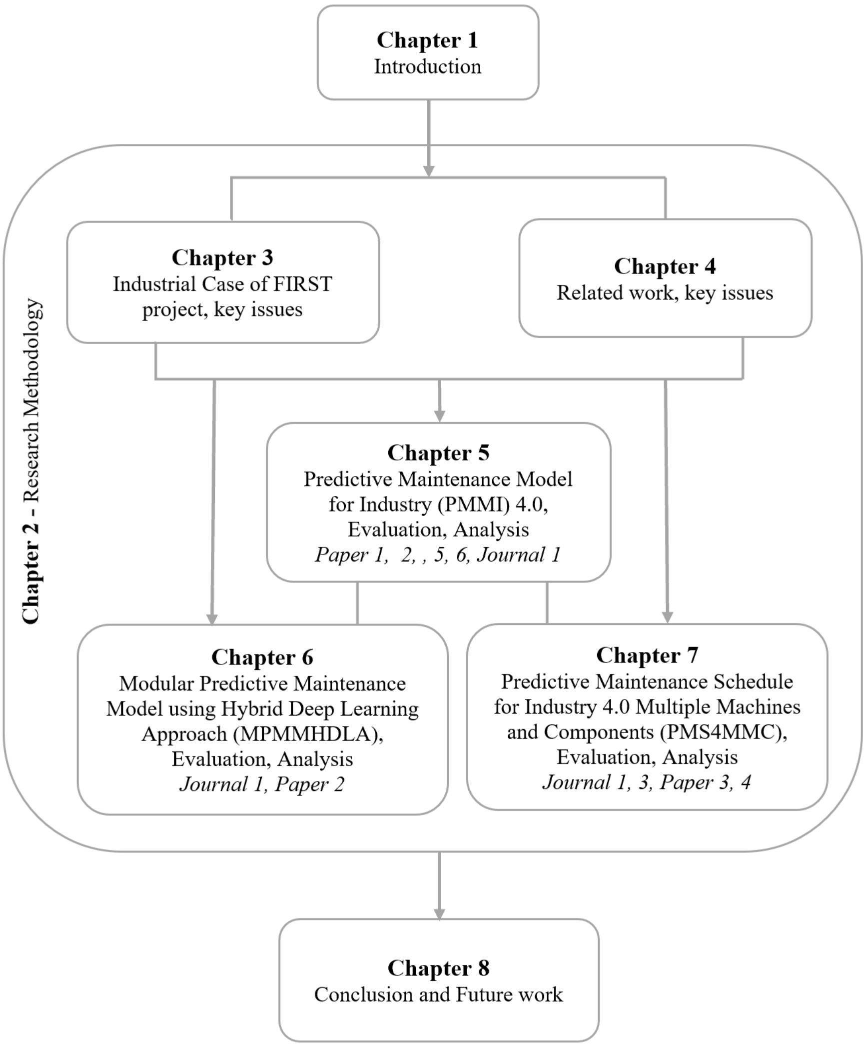


Fig. 1.4 Outline of the chapters, related work and papers

1.5 Publications

This thesis is in addition to papers that have been accepted, presented, and published in journals and the proceedings of conferences. One journal paper is in pending submission process. These publications including a brief description of their contents are presented as below:

Journal 1: Sang, G.M., Xu, L., de Vrieze, P. A Predictive Maintenance Model for Flexible Manufacturing in the context of Industry 4.0. Frontiers in Big Data, section Data Mining and Management Journal (2021)

Journal 2: Sang, G.M., Xu, L., De Vrieze, P. Mid-sized companies in Virtual Factories. A strategy for growth? IM&IO, 2020 (1), 72

Journal 3: Sang, G.M., Xu, L., De Vrieze, P. Industry 4.0 Prescriptive Maintenance for Collaborative Manufacturing Networks, Resilient and Sustainable Manufacturing Networks. Journal of Intelligent Manufacturing (2022)

Paper 1: Sang, G.M., Xu, L., de Vrieze, P., Bai, Y., Pan, F. Predictive Maintenance in Industry 4.0. In: Proceedings of the 10th International Conference on Information Systems and Technologies. pp. 1–11. ACM, New York, NY, USA (2020) https://doi.org/10.1145/3447568.3448537

Paper 2: Sang, G.M., Xu, L., de Vrieze, P., Bai, Y. Towards Predictive Maintenance for Flexible Manufacturing Using FIWARE. Advanced Information Systems Engineering Workshops. CAiSE 2020. Lecture Notes in Business Information Processing, vol 382. Springer, Cham (2020)

Paper 3: Sang, G.M., Xu, L., de Vrieze, P. Supporting Predictive Maintenance in Virtual Factory. PRO-VE 2021 - 22nd IFIP SOCOLNET Working Conference on Virtual Enterprises, Smart and Sustainable Collaborative Networks 4.0, Saint Etienne, France, Unesco Design City, 22-24 November 2021

Paper 4: Sang, G.M., Xu, L., de Vrieze, P., Bai, Y. Applying Predictive Maintenance in Flexible Manufacturing. PRO-VE 2020 - 21st IFIP SOCOLNET Working Conference on Virtual Enterprises, 23-25 November 2020 (2020)

Paper 5: Sang, G.M., Xu, L., de Vrieze, P. Simplifying big data analytics systems with a reference architecture. In: IFIP Advances in Information and Communication Technology (2017)

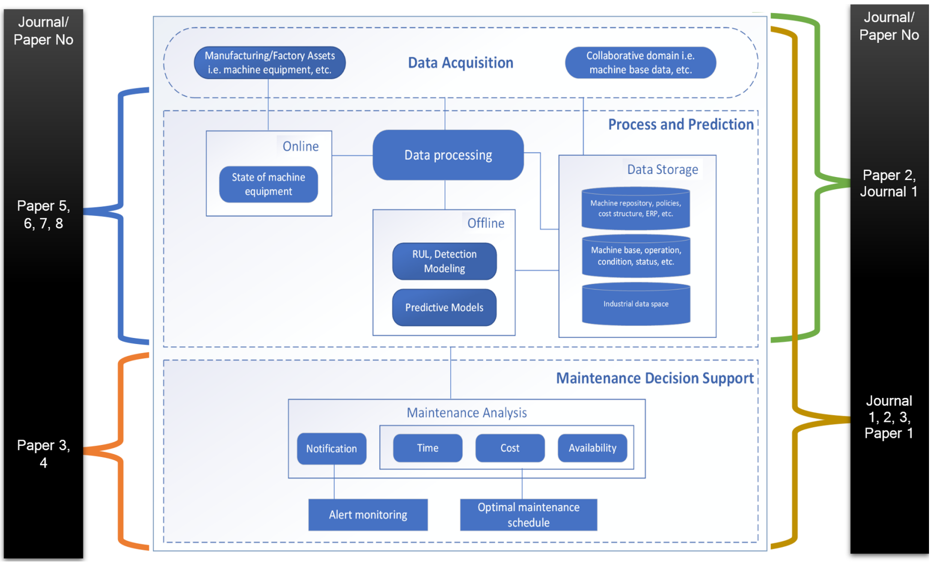


Fig. 1.5 Relation between published papers and research area

Paper 6: Sang, G.M., Xu, L., de Vrieze, P. A reference architecture for big data systems. In: SKIMA 2016 - 2016 10th International Conference on Software, Knowledge, Information Management and Applications (2017)

Paper 7: Sang, G.M., Xu, L., de Vrieze, P. Implementing a Business Intelligence System for small and medium-sized enterprises. In: SQM 2016: 24th International Software Quality Management Conference 21-22 March 2016 Bournemouth, UK

Paper 8: Sang, G.M., Xu, L., de Vrieze, P. Data Analysis Supported Decision Making in Insurance Sector, EWG-DSS 2016 International Conference on Decision Support System Technology, May 23 – 25, 2016, Plymouth, UK

1.5.1 Relationship between the Journals/Papers and the research work i.e. PMMI 4.0 architecture process framework

An overview of the relationship between the publications i.e., journal/papers and the research work i.e., PMMI 4.0, predictive maintenance model for Industry 4.0 process framework is presented in Figure 1.5, while their relationship to the research questions is showed in Table 1.1.

Table 1.1 Relationship between the publications and the research questions

Research questions	Journal 1	Journal 2	Journal 3	Paper 1	Paper 2	Paper 3	Paper 4	Paper 5	Paper 6	Paper 7	Paper 8
Primary question	✓	✓	✓	✓		✓					
Sub-question 1	✓			✓				✓	✓	✓	✓
Sub-question 2					✓		✓				
Sub-question 3	✓					✓	✓				

Chapter 2

Related work

This chapter presents various relevant concepts, work, challenges, and potential requirements related to predictive maintenance for Industry 4.0. The objective is to provide understanding of the state of art offered in various methods, techniques, and frameworks. In Section 2.1, the general aspect of maintenance and issues related to predictive maintenance are presented. The architecture model related to Industry 4.0 predictive maintenance and some issues is discussed in Section 2.2. The key components i.e., predictive model, maintenance schedule, of predictive maintenance as well as some of the key issues are described in Section 2.3 and Section 2.4. In Section 2.5, a summary of related work and some requirements for Industry 4.0 predictive maintenance is presented. Lastly, a chapter summary is provided in Section 2.6.

2.1 Predictive Maintenance

Industry 4.0 enables the collaborative industries in achieving high levels of flexibility and productivity (Thoben et al., 2017). In the context of Industry 4.0 manufacturing, different enterprises can move related business processes beyond its boundary including machines/devices/processes assisted by Industry 4.0 and advanced technologies such as IoT, CPS, etc. In this sense, industrial systems are complex due, in part, to collaborative growing size, and to the integration of new technologies. In other words, there exist several complexities such as the complexity of collaboration, business process, and machine equipment systems. With aging, these systems are subjected to failures, and maintenance activities are hard and expensive. Moreover, the demands of high productivity, profit growth, operational availability, and safety, new innovative tools and methods are required. One of the possible levers consists of maintenance activities (Sang et al., 2021a; Sang, Xu, de Vrieze, Bai and Pan, 2020).

Maintenance is defined as the "combination of all technical, administrative and managerial actions, including supervision actions, during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function" (Mobley, 2002). Well-organized maintenance assists in keeping the life cycle cost down and ensures efficient operations (Sang, Xu, de Vrieze and Bai, 2020*a*). In most industries, a variety of maintenance philosophies are utilized in specific maintenance concepts. The maintenance concept is defined as “the set of various maintenance interventions and the general structure in which these interventions are foreseen” (Mobley, 2002).

In this study, we define predictive maintenance as a collection of activities, methods and services accumulated together to maintain an effective operation, condition, or state of a machine equipment, tool, or system. The different maintenance activities are organized, planned, and executed based on the need of the required maintenance task i.e., repair or replacement based on predictive model such as RUL estimation, as well as business needs. In the context of Industry 4.0 manufacturing, maintenance is directly associated with reducing the costs related with downtime and defective products in the manufacturing industries (Sang, Xu, de Vrieze and Bai, 2020*a*). This means that effective maintenance helps to keep the life cycle cost down and ensures expected operations. By maintaining the system, one can reduce its global life cycle costs, increase its availability, and reduce failure incidents (Sang, Xu, de Vrieze and Bai, 2020*a*).

2.1.1 Predictive and Traditional Maintenance

Maintenance can be distinguished into different categories based on the type of maintenance and complexity into Reactive, preventive, and predictive maintenance as shown in Figure 2.1. *Reactive maintenance* is performed based on the event of system/machine failure and is associated with large and unpredictable downtimes (Mobley, 2002). Thus, it is expensive and subsequently results in losses such as low production and availability.

Traditional Preventive maintenance in which maintenance activities are performed based on a scheduled plan or iteration, or fixed downtime intervals. The repair frequency however can undermine the overall maintenance as the maintenance activity may not always be necessary or inadequate. Moreover, these approaches are not effective in dealing with the demand of Industry 4.0 modern collaborative manufacturing due to cost and management concerns such as low production and availability, inconsistency (Mobley, 2002; Sang, Xu, de Vrieze, Bai and Pan, 2020).

Predictive maintenance is based on data-driven methods and maintenance activity is scheduled in advance and acted before a failure event occurs (Mobley, 2002). A data-driven approach uses big data (operation, failure, etc.) collected from sensors, high computation and

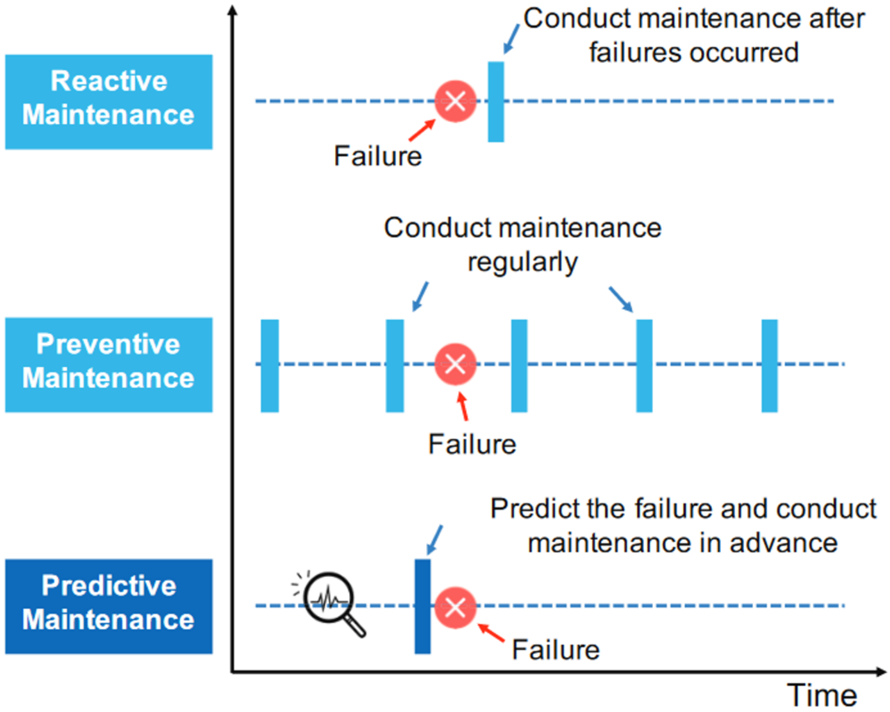


Fig. 2.1 Difference between Predictive and Traditional maintenance (Ran et al., 2019)

advanced machine learning (Mobley, 2002). Thus, it offers advanced analytics and a cost-effective option, compared with traditional approaches such as model-based or experience-based methods which are based on physical failure models or experience, and hence are highly complex, difficult to build and maintain (Mobley, 2002). Moreover, both traditional maintenance approaches (reactive, preventive) face many challenges such as Industry 4.0, complexity of collaboration, big data, and computation (Mobley, 2002; Sang, Xu, de Vrieze, Bai and Pan, 2020). On the other hand, predictive maintenance is based on data-driven methods and maintenance activity is scheduled in advance and acted before a failure event occurs (Mobley, 2002). Using data such as operation, condition, or time series (sequential) data, predictive models are built to capture information patterns which then can be utilized for predictive maintenance dealing with maintenance activities and schedule plan.

Generally, predictive maintenance 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 (Sang, Xu, de Vrieze, Bai and Pan, 2020). Besides, the application of predictive maintenance approaches in manufacturing industries can reduce maintenance costs up to 30% and eliminate breakdowns up to 75% in comparison to conventional preventive maintenance (Gao et al., 2015).

2.1.2 Predictive Maintenance Approach

The approach to dealing with predictive maintenance can be classified into three: model-based, knowledge-based, and data-driven (Mobley, 2002). The model-based relies on the physical structure of machine equipment tools which is then used for the different parameters required for building mathematical model (Mobley, 2002). Thus, it requires expert engineers who has knowledge about the machine tools and configurations as well as building the required model. The reliance on the degradation model of physical structure to learn the equipment health state, makes it to be inefficient in dealing with constraints such as complex equipment structure, for example the complex systems operating in the context of Industry 4.0 (Sang, Xu, de Vrieze, Bai and Pan, 2020; Tobon-Mejia et al., 2012).

The experience-based methods use mainly the data of the experience feedback gathered during a significant period of time (maintenance and operating data, failure times, etc.) to adjust the parameters of some reliability models such as Weibull, exponential, etc. (Tobon-Mejia et al., 2012). Thus, these methods are slow, and costly as the corresponding results of machine/component operation, which is enough to generate the appropriate feedback.

To overcome the challenges posed by model-based and experience-based prognostics, data-driven approaches are based on data e.g. sensor measurement, operational, to build the prediction model without the knowledge of physical structure (Mobley, 2002; Sang, Xu, de Vrieze, Bai and Pan, 2020; Tobon-Mejia et al., 2012). The data-driven prognostics methods deal with the transformation of the data provided by the sensors into reliable models that capture the behavior of the degradation.

Another approach, fusion which utilized both model-based and data-driven methods can be considered (Tobon-Mejia et al., 2012). As the model-based still relies on the physical structure which tends to be undiscovered intricacy, it is still problematic (Sang, Xu, de Vrieze, Bai and Pan, 2020; Tobon-Mejia et al., 2012). As such, data-driven methods have been proven to be an effective approach for example predictive RUL model (Tobon-Mejia et al., 2012).

2.1.3 Difference between predictive maintenance and prescriptive maintenance

In the context of Industry 4.0, many different data i.e., big data are collected from different domains and sources. Since traditional data processing and tools are inefficient for dealing with Industry 4.0, advanced technologies such as big data analytics, are required (Sang et al., 2017; Sang, Xu, de Vrieze and Bai, 2020*a*). Big data analytics as illustrated in Figure 2.2

facilitates different business analytic solutions for assisting decision making (Porter and Heppelmann, 2014; Sang et al., 2016*c*).

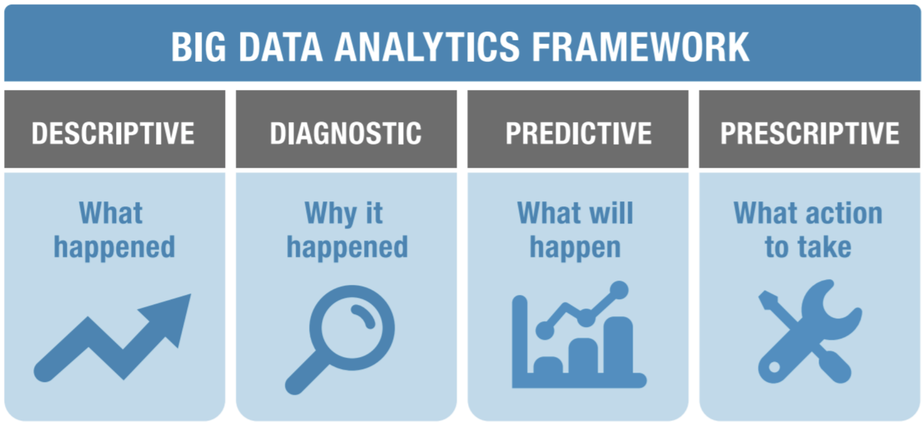


Fig. 2.2 Big data analytics framework depicting different analytics capabilities (Biros et al., 2021)

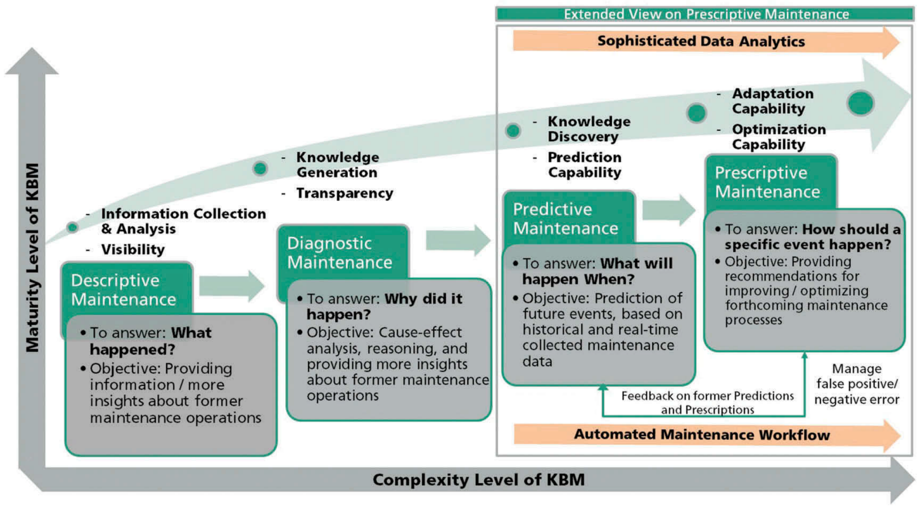


Fig. 2.3 Maturity and complexity levels of Knowledge Based Management (Ansari et al., 2019)

Maintenance analytics can be distinguished into four different capabilities, depicting the maturity and complexity level as illustrated in Figure 2.3 (Ansari et al., 2019). Descriptive i.e., what happened (a failure event of machine/component) and Diagnostic i.e., why happened (cause of machine/component failure) maintenance can be accommodated by traditional systems such as MES ERP, etc. (Mobley, 2002). And both descriptive and diagnostic tend to associate with reactive maintenance which can be costly, time consuming and inefficient, particularly for Industry 4.0.

In the case of predictive and prescriptive maintenance, advanced capabilities such as big data, deep learning, etc., are required in dealing with the complex and increasing data and systems exist in advanced manufacturing organization (Sang et al., 2017, 2021*a*). Predictive maintenance is based on data-driven methods and maintenance activity is scheduled in advance and acted before a failure event occurs (Mobley, 2002; Sang, Xu, de Vrieze and Bai, 2020*a*). Data-driven approach utilizes big data (operation, failure, etc.) collected from sensors, high computation and advanced techniques such as deep learning (Mobley, 2002; Sang, Xu, de Vrieze and Bai, 2020*a*). This enables future detection of a failure event and any maintenance activity can be planned and acted (Mobley, 2002; Sang, Xu, de Vrieze and Bai, 2020*a*).

As illustrated in Figure 2.3, prescriptive maintenance extends predictive maintenance by offering more information regarding maintenance actions, associated cost in a more detailed analysis. This requires the utilization of advanced capabilities, big data, deep learning, etc. that generates different maintenance options for assisting decision making. In our study, we consider the aspect of prescriptive maintenance for designing the Industry 4.0 predictive maintenance scheduling.

2.1.4 Some Key Issues of Predictive Maintenance

Based on the discussion described above and existing approaches, there exist several challenges in predictive maintenance and its data management and complexity (Krupitzer et al., 2020; Mobley, 2002; Provost and Fawcett, 2013; Ran et al., 2019; Sang et al., 2017, 2021*a*; Sang, Xu, de Vrieze, Bai and Pan, 2020; Susto et al., 2012; Zonta et al., 2020):

- More complex system i.e., multiple machines/components, robots, CPS, etc., involved in Industry 4.0
- Diverse and voluminous data domains/sources
- Application of emerging technologies such as Big data analytics, AI/Deep learning as traditional methods cannot handle the demands of Industry 4.0
- Downtime and associated cost for factory operation and collaborative network chain, particularly in the context of Industry 4.0 manufacturing.
- Cost and setup including sensor enabled machine tools, maintenance resource such as engineer, spares, etc.

We compiled some of the different aspect such as as issues, advantage, etc. regarding maintenance from the related-work as presented in Table 2.1.

Table 2.1 Summary of maintenance

Maintenance	Advantage	Issues i.e. challenges	Data-driven
Reactive (Mobley, 2002; Sang, Xu, de Vrieze, Bai and Pan, 2020; Tobon-Mejia et al., 2012)	Maximum utilization and production value	Unplanned downtime	No
	Lower prevention cost	High spare parts inventory cost	Failure event-based
	Typical application	Potential further damage for the equipment	
	Redundant, or non-critical equipment	Higher repair cost	
	Repairing equipment with low cost after breakdown	Industry 4.0 application	
Preventive (Mobley, 2002; Sang, Xu, de Vrieze, Bai and Pan, 2020)	Lower repair cost	Need for inventory	No
	Less equipment malfunctions and unplanned downtime	Increased planned downtime	Regular plan or experience
	Typical application	Maintenance on seemingly perfect equipment	
	Have a likelihood of fail-ure that increases with time or use	Industry 4.0 application	
Predictive (Mobley, 2002; Sang, Xu, de Vrieze, Bai and Pan, 2020; Tobon-Mejia et al., 2012)	A holistic view of equipment health	Increased upfront infrastructure	Yes
	improved analytics options	cost and setup (e.g., sensors)	
	Avoid running to failure	more complex system	
	Typical application		
	Have failure modes that can be cost-effectively predicted with regular monitoring		

2.2 Industry 4.0 Predictive Maintenance Architecture

2.2.1 Predictive Maintenance and Industry 4.0

2.2.1.1 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 behaviors to changing orders and operating conditions through self-optimization and reconfiguration" (Industry 4.0, n.d.; Sang, Xu, de Vrieze and Bai, 2020*a*).

Industry 4.0 is being regarded by the existence of several components interactions among interconnected devices i.e. sensors, computation services, etc. (Thoben et al., 2017). Essentially the data exchanged and produced in such interaction among several components establishes the underlying business processes (Sang, Xu, de Vrieze and Bai, 2020*a*).

Manufacturing industries are moving towards adopting the Industry 4.0 concept for achieving effective smart solutions (Qin et al., 2016). Industry 4.0 supports the flexibility required for the collaborative network by the application of advanced technologies. In this aspect, the internet of things (IoT), Cyber Physical Systems (CPS), big data analytics, cloud computing, etc. are utilized for operating the intelligent machines and processes in the collaborative context (Koren et al., 2018; Thoben et al., 2017). In Industry 4.0 context, manufacturing processes are moved across factories and enterprises to manage the production life cycle and demands effectively (Sang, Xu, de Vrieze, Bai and Pan, 2020). With the huge amount of heterogeneous data generated by various connected devices such as sensors pose both challenges and opportunities such as data driven analytics (Sang, Xu, de Vrieze and Bai, 2020*a*).

There however exist several challenges such as the maturity i.e. the level of readiness for implementing Industry 4.0 and related issues including modularity, interoperability, and handling of business data across the different domains, and advanced big data analytics for the optimization of processes and components (Gröger, 2018; Sang, Xu, de Vrieze, Bai and Pan, 2020).

2.2.1.2 Industry 4.0 Maturity Model

The maturity i.e. the level of readiness for implementing Industry 4.0 may be measured by different ways across the industries (Jarrahi et al., 2017; Lichtblau et al., 2015; Machado et al., 2019; Qin et al., 2016; Schuh et al., 2020*a*; Schumacher et al., 2016; VanBoskirk and Gill, 2016; Wiesner et al., 2018). Brozzi et al. (2018); Jarrahi et al. (2017); Lichtblau et al. (2015); Qin et al. (2016); Schumacher et al. (2016); Wiesner et al. (2018) assess the readiness

Table 2.2 Four Business Areas and Its Guiding Principles (Schuh et al., 2020*a*)

Structural area	Guiding principles
Resources	Digital capability Structured communication
Information systems	Self-learning information processing Information system integration
Organizational structure	Organic internal organization Dynamic collaboration within the value network
Culture	Willingness to change Social collaboration

for implementing Industry 4.0 across different organizations and conclude that there still exists a lack of coherent solutions, especially in the capability of technologies such as big data analytics, and collaboration. Schuh et al. (2020*a*) outline four areas that can be used for better assessment of Industry 4.0 maturity as shown in Table 2.2. It considers a more holistic approach including an emphasis on organizational issues, which is important when it comes to implementation of Industry 4.0 enabling technologies.

Machine equipment tools, materials, products as well as human resources are considered for the *Resources*. The *digital capability and structured communication* involve resources for information-based working and its interaction with each other, respectively. *Information systems* includes the aspect of data analytics that can support decision making, specifically in self-learning information processing and information system integration. This facilitates the integration and availability of information for supporting decision making.

Organizational structure addresses the business processes both internally and externally. Thus, information sharing across organizations and dynamic collaboration within the value network are important aspect of the organization. *Culture* refers to the general aspect of the organizational adaptability and collaboration, specifically its values and employees. This is supported by the technological solutions utilizing available information.

Considering the four business areas, different steps as shown in Figure 2.4 can be used for assessing Industry 4.0 maturity. The aspect of digitalization includes smart device i.e. the internet of things and connectivity i.e. interoperability which provides a basis for development. It requires different systems to work together utilizing and producing data where a high degree of interoperability is required for the different systems.

Since the Industry 4.0 paradigm is based on digitalization and collaboration, (Schuh et al., 2020*a*) outline different aspects: the *visibility* is supported by the availability of information from the integration of the different systems, the *transparency* facilitates reliable information from the aggregation of available data and information, the *predictive capacity* enables better supporting decision-making using the available data, and the *adaptability* supports certain decisions to be made autonomously. Along with the progress stage by stage, Industry 4.0 technological landscape shifts from an organization to cross-organizations digitalization which allows flexible integration both horizontally and vertically.

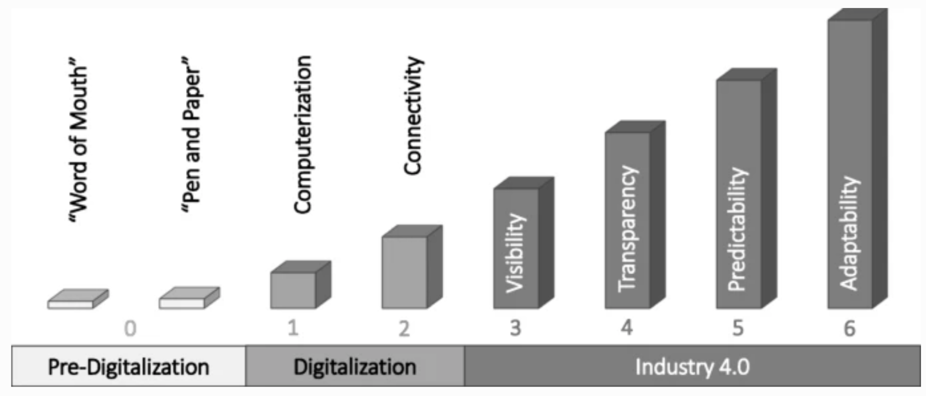


Fig. 2.4 Industry 4.0 Maturity Model (Schuh et al., 2017)

2.2.1.3 Predictive Maintenance in Industry 4.0 Maturity

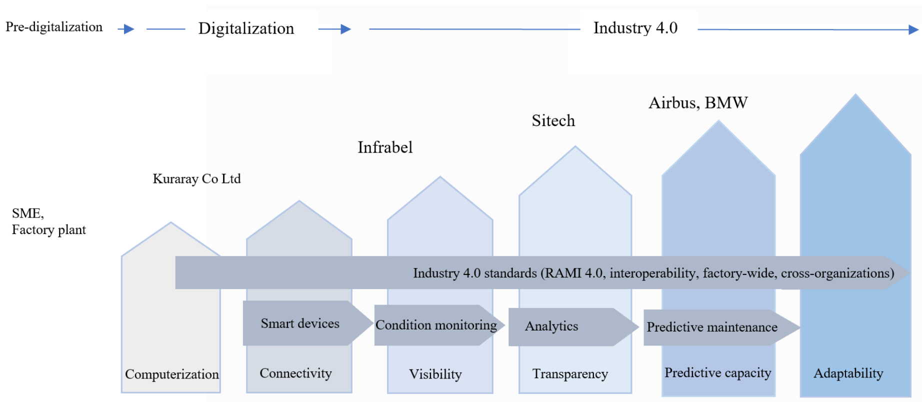


Fig. 2.5 Predictive Maintenance in Industry 4.0 Maturity Mapped with Example Companies

Figure 2.5 (adapted from the Industry 4.0 Maturity Model Schuh et al. (2017)) illustrates the example companies who have implemented the capability of predictive maintenance that are mapped with different levels of Industry 4.0 maturity. Industry 4.0 standards including reference architecture model for industry (RAMI) 4.0, interoperability i.e., integration of different systems both factory-wide and cross-organizations, serve as the basis for Industry 4.0 predictive maintenance maturity.

For the *pre-digitalization* level, companies such as traditional manufacturing, SME or Factory plant who have limited capability of technologies and information systems. In the context of maintenance, it is usually based on preventive i.e., routine which is based on model-driven (i.e., based on the physical structure and degradation of system) and thus is limited (Mobley, 2002).

In the *digitalization* level, the connectivity and computerization are supported by streamlining business processes using technologies. Kuraray Co Ltd is a global specialty chemicals manufacturer, one of the largest suppliers of polymers and synthetic microfibres (Schuh et al., 2020*b*). Kuraray's three sites in Germany form a production chain for products such as laminated safety glass interlayers. Predictive maintenance is mostly based on model-driven as well as using MES in each site. It still lacks the integration of systems and smart devices such as sensor as well as a coherent platform for the production chain, particularly in coordinating activities such as maintenance.

In *Industry 4.0* level, Infrabel and Sitbell initiate predictive maintenance in the context of Industry 4.0. Infrabel is the state-owned company responsible for Belgian rail infrastructure (Mark and Mulders, 2017). Recently, Infrabel has started investing in the management, maintenance, and development of rail infrastructure. This includes installation of condition monitoring tools such as measurement of trains for inspecting tracks, sensors for detecting overheating in shaft sleeves on passing trains; and meters to detect drifts in power consumption, which usually occur prior to mechanical failures in switches. However, the application of these collected large-scale data for predictive maintenance is still in progress due to various reasons including fragmented maintenance organization, regulations.

Sitech offers asset management i.e., maintenance for factory located at Chemelot, a site for the chemical industry in Limburg, the Netherlands (Mark and Mulders, 2017). Currently, it utilizes sensor data collected from the factory to assist in maintenance. For example, predicting contamination for a drying column in the factory is done by utilizing anomaly detection driven by sensor data such as air-temperature. One challenge however is that applying predictive maintenance predictive maintenance all critical and semi-critical equipment in the entire factories and to the whole site.

In the case of Airbus, it utilizes the monitoring data of aircraft engine's operation at its fleet for building predictive models that assists in maintenance (Airbus, 2022). Predictive maintenance model is designed for its specific different aircraft models, supporting maintenance across its plants.

At BMW, it recently adopts a cloud-based approach that sensor devices are used to monitor and collect data from its manufacturing plant (Pressclub Canada, 2021). The collected data are then used for predictive maintenance, better maintenance planning. Currently, predictive maintenance is used in the mechanical drivetrain production, bodyshop and vehicle assembly for detection of anomalies.

Currently, Airbus and BMW focus on limited equipment within its own organization for their capabilities. Thus, the consideration for Industry 4.0 standards as well as flexibility for factory-wide or cross-organizations are still to be addressed.

Overall, based on the studies of predictive maintenance capability across industries carried out by Machado et al. (2019); Mark and Mulders (2017); Qin et al. (2016); Schuh et al. (2020*a*,*b*); Schumacher et al. (2016), the Industry 4.0 maturity across different companies is at the digitalization level and at early level of Industry 4.0. Most organizations have some extent of the digitalization capabilities i.e. predictive maintenance within the organization itself but lack the level in which Industry 4.0 standards, factory-wide or cross-organizations are considered.

One key challenge is the flexible integration of different systems at different levels including business process, smart systems/devices as well as the enormous generated data across factory-wide and organizations. This requires a high degree of interoperability, leading to Industry 4.0 maturity levels such as predictive capability and adaptability.

2.2.2 Interoperability for Industry 4.0

Interoperability is essentially important for operating across digital manufacturing platforms (Xu et al., 2019). Many different manufacturing organizations operating with mixed heterogeneous systems by using different platforms, vendor specific technologies, or closed standards (Wajid and Bhullar, 2019). Often,the involved platforms and technologies are closed in nature of commercial reasons, which creates interoperability issues particularly concerning cross platform connectivity, utilization of software applications, and data across multiple platforms (Wajid and Bhullar, 2019).

A platform interoperability framework is illustrated in Figure 2.6 which is designed for interoperability of vertical digital manufacturing platforms (Wajid and Bhullar, 2019). A three-tier hierarchy includes the platform tier at the bottom, the application tier at the middle, and the integration tier at the top.

The platform tier focuses on the separation of *identification* from *services* to allow shared access across different platforms. Approaches for single sign-on, policy-based access and user right management can all contribute towards interoperability at this level (Wajid and Bhullar, 2019). The application tier should focus on to sharing the application and services with users with right to access the platforms, either locally or through remote access (Wajid and Bhullar, 2019). The integration tier can deal with heterogeneous standards, interfaces, and communication protocols. The use of standards at all stages of the information/data

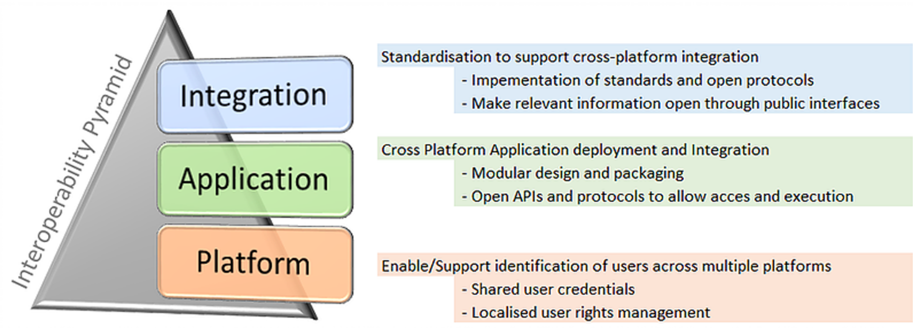


Fig. 2.6 Interoperability Framework for Digital Manufacturing Platforms (Wajid and Bhullar, 2019)

flow can allow the applications, tools, and services to be interoperable in an ecosystem environment (Wajid and Bhullar, 2019).

In general, the platform tier could be control by the shared access across different platform, which is not always could be supported by the Flexible Manufacturing and virtual factory management in the FIRST project. Some of the applications and services at the application tier are described as manufacturing assets in the FIRST project. The services including maintenance at the integration tier can be treated as the manufacturing services or the main services at the interoperability framework in the FIRST project.

2.2.2.1 Interoperability of Predictive Maintenance and Industry 4.0

In the context of Industry 4.0 manufacturing, predictive maintenance offers a prognosis of faults in related machineries and deficient processes using various analyses (Sang, Xu, de Vrieze and Bai, 2020*a*). Predictive maintenance utilizes the data (i.e., big data) generated by the different systems, processes, and machine equipment tools of Industry 4.0 for various analytics such as predictive models, etc. (Sang, Xu, de Vrieze and Bai, 2020*a*).

The integration and interaction of those different systems, processes and machine equipment tools are facilitated by different interfaces. In this context, Lee at al (2015) provides a CPS reference architecture which describes the different levels for a cyber physical system as shown in Figure 2.7 (Lee et al., 2015). In this context, there are different adapters for data interaction from different levels, i.e., components, machines, systems. For Industry 4.0, the data interaction extends to collaborative systems, processes, or business partners such as suppliers and customers. These collaborative interactions normally are dealt with different data models for each own requirement which do not normally consider for interoperability.

For Industry 4.0 predictive maintenance, the different levels of integration and interaction should be considered, thus industry 4.0 standards (5C does not consider interoperability

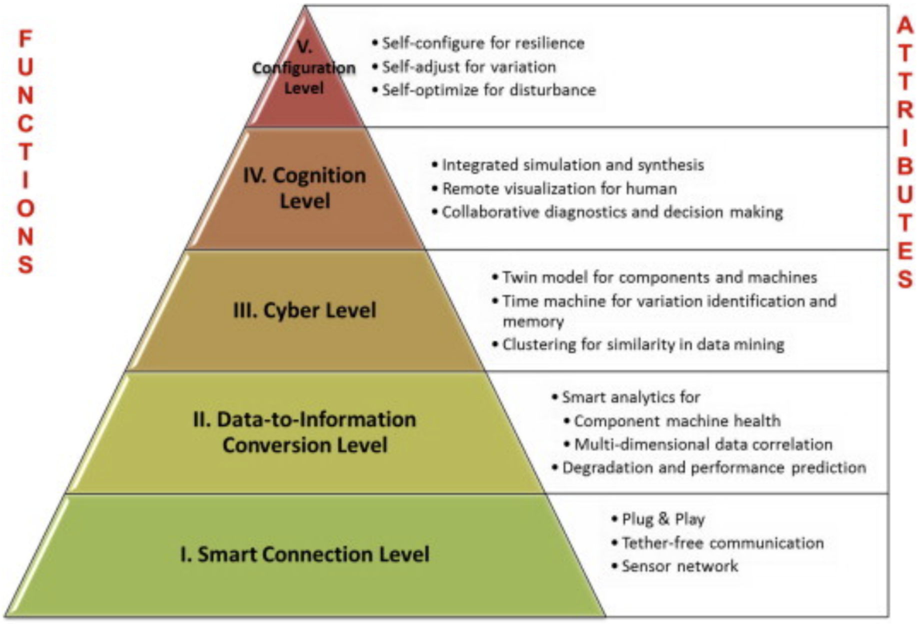


Fig. 2.7 5C architecture for implementation of Cyber-Physical System (Lee et al., 2015)

i.e., standardization, implementation level, etc.) which facilitates interoperability of the different systems, processes, and machine equipment tools both internally (its own business organization) and externally (across collaborative organizations).

Since traditional data processing and tools are not efficient for dealing with the complex and increasing data generated by Industry 4.0 manufacturing system (Sang et al., 2017; Sang, Xu, de Vrieze and Bai, 2020*a*), organizations are turning towards Industry 4.0, particularly the aspect of interoperability. High interoperability leads to the ease integration of advanced capabilities such as big data processing and tools and advanced methods such as deep learning, etc., which are required for the different aspect of predictive maintenance services (Sang et al., 2021*a*).

2.2.3 Architecture Model for Industry 4.0

Industry 4.0 operates with many different systems, processes, machines tools including CPS, IoT, etc., and thus is complex. This requires an architecture model which assists in providing a conceptual or abstract description of the complex systems, processes, etc., for better understanding and implementation. There are various architecture models i.e., RAMI 4.0, IIRA, etc., which focus on different aspect of Industry 4.0. Reference architecture model industry (RAMI) 4.0 focus on the wider aspect of Industry 4.0, considering the digitalization of the various enterprises/systems/processes etc., involved in the network chain whereas

IIRA rather focuses on the organization itself. Thus, RAMI 4.0 architecture model would benefit for manufacturing organizations such as the application cases, who operate in complex collaborative manufacturing network whereas IIRA would address one organization's concern regarding implementing IoT system within the organization.

In general, a coherent predictive maintenance architecture would offer a simplified view of Industry 4.0 and facilitate the abilities to easily integrate data from different machines, devices, and systems as well as to easily deploy IoT sensors for monitoring and different services which are embedded and optimized with operation and production processes which could achieve optimization for maintenances (Sang et al., 2021*a*; Sang, Xu, de Vrieze and Bai, 2020*a*).

We describe RAMI 4.0 and IIRA in the next section.

2.2.3.1 Reference Architecture Model Industry (RAMI) 4.0

Reference Architecture Model Industry (RAMI) 4.0 simplifies the Industry 4.0 revolution by providing a three-dimensional model that describes different complex components, sub-models, and processes (Industry 4.0, n.d.; Sang, Xu, de Vrieze and Bai, 2020*a*). The three-dimensional model includes hierarchy levels, architecture layers and lifecycle value stream as shown in Figure 2.8.

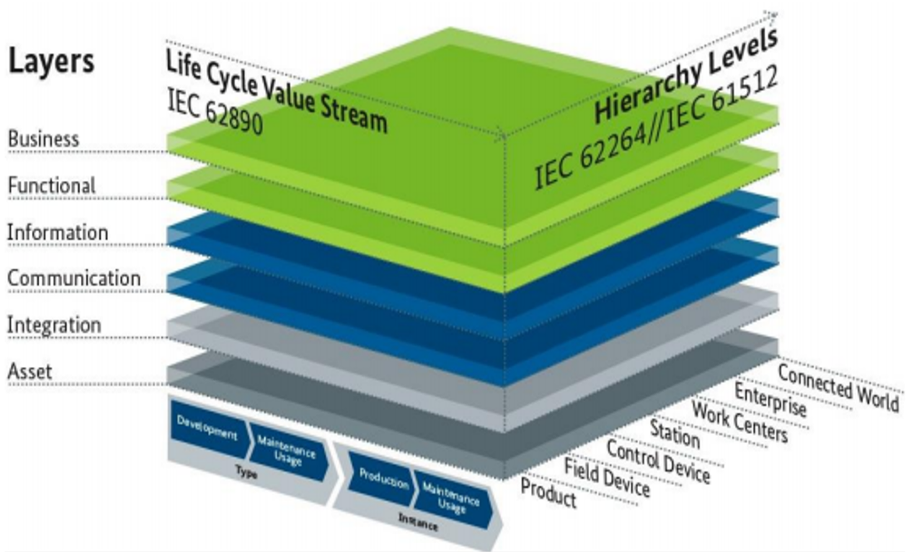


Fig. 2.8 Reference Architecture Model Industry 4.0 (Industry 4.0, n.d.)

- The hierarchy levels represent the factory levels including collaborative organizations and factories, devices, goods, suppliers and customers (i.e. product, field and control device, work centers, enterprise and connected world) (Zezulka et al., 2016).

- 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 (Thoben et al., 2017; Zezulka et al., 2016). 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 (Gröger, 2018; Thoben et al., 2017; Zezulka et al., 2016).

For Industry 4.0 predictive maintenance, RAMI 4.0 can assist in simplifying the complex systems, processes, etc. involved in Industry 4.0 manufacturing chain (Sang, Xu, de Vrieze, Bai and Pan, 2020). A flexible and consistent architecture platform is essential to modern Industry 4.0 systems like those in complex and dynamic manufacturing domains (Sang, Xu, de Vrieze and Bai, 2020*a*). It is essential to effectively operate and manage the whole cycle of the production chain. To cope with the complexity of Industry 4.0, designing predictive maintenance architecture in RAMI 4.0 would potentially facilitate the understanding of the industry operations, partners, communication, and the underlying technologies in a consistent and simplified view of Industry 4.0 with different components and processes (Sang, Xu, de Vrieze and Bai, 2020*a*).

There remains a lack of coherent mapping and modelling of components, processes of RAMI 4.0 in manufacturing operations, specifically in real world implementation (Industry 4.0, n.d.; Thoben et al., 2017).

2.2.3.2 Industrial Internet Reference Architecture (IIRA)

As previously described, IIRA could address some of the concerns such as stakeholders, viewpoints, etc., regarding IoT systems within an organization. It could provide the linkage and mapping between the requirements and the intended IoT systems.

IIRA offers a common architecture framework which can be used for the development of an interoperable the internet of things (IoT) systems for diverse applications across a broad spectrum of industrial verticals in the public and private sectors to achieve an IoT. Essentially, IIRA is an abstract reference model for dealing with industrial internet of thing systems (Lin et al., 2017). It defines an Industrial Internet Architecture Framework that contains viewpoints and concerns to assist in the development, documentation, and communication of the IIRA as shown in Figure 2.9.

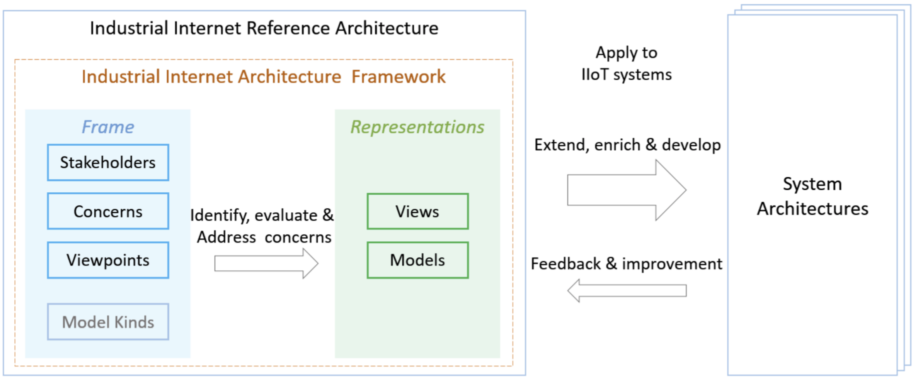


Fig. 2.9 IIRA reference architecture (Lin et al., 2017)

The outcome of implementing the IIRA to the different aspect of the IoT systems are documented. First, the architectural concerns regarding IoT systems are identified. In this context, viewpoints along with their respective stakeholders across industrial sectors are considered. The identified concerns are then analyzed for producing an abstract architecture representation that may provide guidance to resolve these concerns in these viewpoints. Figure 2.9 illustrates the key ideas about the constructs of the Industrial Internet Reference Architecture and its application.

2.2.4 Implementation Platform for Industry 4.0 Architecture Model

RAMI 4.0 and IIRA are concerned with the aspect of architecture model which can offer a better understanding and design of complex Industry 4.0 systems. Both architectures provide the conceptual model which leads to an architecture implementation. Thus, both architectures do not consider the implementation aspect. FIWARE, however is an implementation of Industry 4.0 solution which focuses on a modular and open framework (Fiware, n.d.*b*,n; Sang, Xu, de Vrieze, Bai and Pan, 2020).

FIWARE is an open-source framework for building advanced solutions. These solutions are supported by gathering data from many different sources to process and analyse that information to implement the desired intelligent behaviour (Fiware, n.d.*b*,n; Sang, Xu, de Vrieze, Bai and Pan, 2020). There are five components, namely context processing, analysis, and visualization at the top of Figure 2.10; core context management (context blocker) at the middle top of Figure 2.10; Internet of Things (IoT), robots and third-party systems at the bottom of Figure 2.10; data/API management, publication, and monetization at the right of Figure 2.10; and development tools at the left of Figure 2.10 (Sang, Xu, de Vrieze, Bai and Pan, 2020).

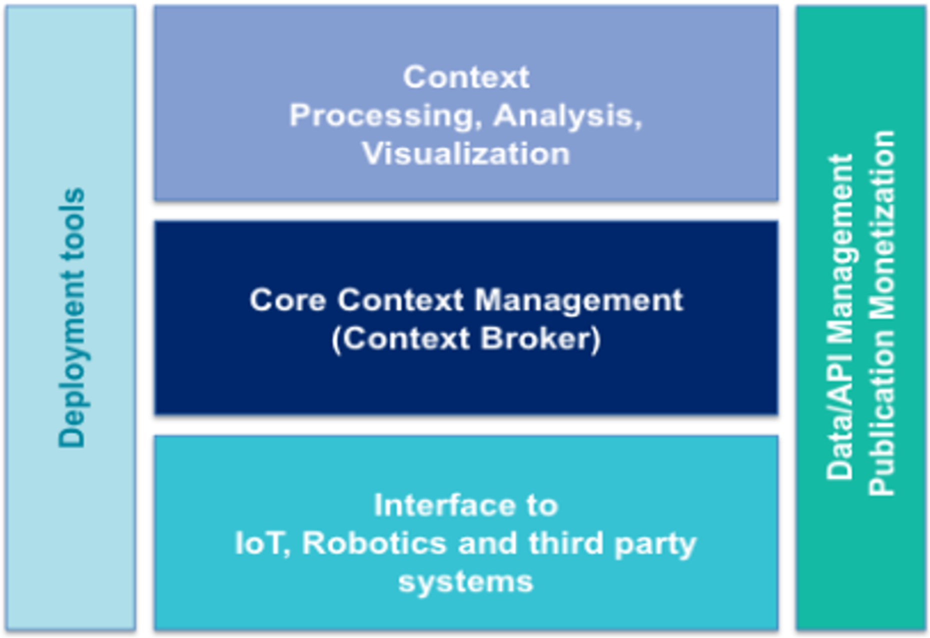


Fig. 2.10 FIWARE platform architecture overview (Fiware, n.d.*b*)

- Context processing, analysis, and visualization of context information for supporting to usage control and the opportunity to publish and monetize part of managed context data.
- Core Context Management (Context Broker) facilitates to managing and gathering context information at large scale enabling context-aware applications with the context information model (Fiware, n.d.*b*,n).
- Internet of Things (IoT), robots and third-party systems, defines interfaces for capturing updates on context information and translating required actuations.
- Data/API management, publication, and monetization, implementing the expected smart behaviour of applications and/or assisting end users in making smart decisions.
- Deployment tools for support of easing the deployment and configuration of FIWARE or third-party components and their integration with FIWARE Context Broker technology.

There are several FIWARE GEs that can be integrated based on business needs (Sang, Xu, de Vrieze, Bai and Pan, 2020). These components include (Fiware, n.d.*b*; Sang, Xu, de Vrieze, Bai and Pan, 2020):

- Components such as applicationsOrion, STH-Comet, Cygnus, QuantumLeap, Draco) for development of context-aware;
- IDAS, OpenMTC, for connection to the Internet of Things;
- Components such as Perseo for real-time processing of context events;
- Keyrock, Wilma, AuthZForce for handling authorization and access control to APIs;
- Components such as CKAN extensions, Data/API Biz Framework, IDRA for publication and monetization of context information;
- Wirecloud for example for creation of dashboard applications;
- Kurento for real-time processing of media streaming;
- Component such as Knowage for business intelligence;
- Fast RTPS, Micro XRCE-DDS for connection to robots;
- Cosmos for big data context analysis;
- FogFlow for cloud edge;
- Domibus for documents exchange.

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 (Sang, Xu, de Vrieze, Bai and Pan, 2020).

With increasing application of IoT devices, the ability to support not only open standards but also dynamic data becomes critical (Sang, Xu, de Vrieze, Bai and Pan, 2020). 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 systems or devices, enables the information to actuate and therefore alter or enrich the current context in the context of flexible manufacturing platform (Sang, Xu, de Vrieze, Bai and Pan, 2020).

The FIWARE context broker serves as the platform's core component that interacts with different systems, processes, devices (Fiware, n.d.*b*). It facilitates managing the updates and access to the current state of context. In this context, the process is supported by a suite of different components, which may be supply context data from diverse sources such as ERP system, mobile apps or IoT sensors for example, supporting processing, analysis and visualization of data or bringing support to data access control, publication, or monetization (Fiware, n.d.*b*; Sang, Xu, de Vrieze, Bai and Pan, 2020).

2.2.4.1 Advanced Analytics Capabilities for Predictive Maintenance

As the manufacturing process such as the application cases (i.e. chapter 3), becomes more and more complex, it is hard to effectively identify the problems arising in the manufacturing process by the traditional approach. These potential maintenance problems in modern manufacturing can be detected by the application of advanced analytics such as big data analytics, deep learning, etc. The big data analysis enabled component in conjunction with both real-time and batch processing enables in dealing with big data collected from sensors is important for the industries to respond to the maintenance issues potentially arise in the manufacturing network more effectively, in comparison with the traditional maintenance approaches that rely on reactive or preventive strategies based on model-based or experience-based methods (Mobley, 2002; Sang et al., 2021*a*).

Besides, for better predictive maintenance, implementing predictive models trained from different data sources such as historical/sensor operational and machine data and shared data such as manufacturer data is necessary, to provide better management i.e., predictive maintenance, maintenance decision making, etc., of the condition and process of expensive manufacturing equipment and optimization of the whole production chain. In this way, advanced analytics such as big data analytics brings more efficiency, sharper insight, and more intelligence to the collaborative manufacturing chain, compared to the traditional approaches such as model-based or experience-based, which rely on domain experts or the physical structure and degradation of the systems/machines tools (Sang, Xu, de Vrieze and Bai, 2020*a*).

Moreover, commercial cloud approaches such as AWS, Azure, Google, etc., could also provide different solutions to different business cases. However, these platforms mostly still ignore the nature of modularity and open framework that is highly important for dynamic and complex Industry 4.0 predictive maintenance (Sang et al., 2021*a*; Yan et al., 2017). Key different components such as scalable databases, identity, or API management, etc., of these commercial approaches could benefit the different business needs that can be integrated into a flexible architecture platform.

2.2.5 Key Issues related to architecture model for Industry 4.0 Predictive Maintenance

Based on the challenges and maturity of Industry 4.0 discussed in previous sections, there exist several challenges to designing and implementation of predictive maintenance.

Table 2.3 Summary of existing architecture models for predictive maintenance

Approach	Short Description	Big Data capability	Consider for flexible/modular platform
A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems (Lee et al., 2015)	based on 5-levels(Configuration, Cognition, Cyber, Conversion, Connection) architecture for manufacturing Industry 4.0	yes	Limited, general guidelines and focus on architecture for CPS
IIRA (Lin et al., 2017)	based on viewpoint, concern intended for IoT systems	No	Limited, general guidelines and focus on architecture for IoT
RAMI 4.0 (Zezulka et al., 2016)	based on three-dimensional model representing different complex components, sub-models, and processes	Yes	Yes, general guidelines and focus on architecture for IoT
RAMI 4.0 architecture based Predictive Maintenance (Bousdekis et al., 2019)	mainly focus on RAMI 4.0 architecture design and its usage	No	Limited, general guidelines and focus on architecture for IoT
A unified predictive maintenance system (Hribernik et al., 2018)	driven by big data and innovation i.e. service and smart analytics	Yes	Limited, generally focus on big data enabled service and analytics
Cloud-enhanced predictive maintenance (Schmidt et al., 2017)	based on cloud computing focusing on data processing	Yes	Limited, generally focus on focus on cloud big data processing etc.
Architecture of a Predictive Maintenance Framework (Groba et al., 2007)	based on integration of ERP, MES and other information systems and data processing	No	No, generally focus on enterprise systems such as ERP, MES, etc.

Flexible architecture: since several different systems, processes and machine equipment tools operate in Industry 4.0 manufacturing context, a simplified architecture which is flexible enough to support the dynamic nature and demands of Industry 4.0.

To support flexible architecture, the different systems, processes, and machine equipment tools should be integrated for business operation. Thus, this requires high degree of interoperability. ***Interoperability*** facilitates the ease integration of different systems, processes and machine equipment tools required for business requirements.

Modularity, the capability of enabling plugin or re-configure processes, devices, machines without a need for extensive re-development/engineering effort, is essentially important to enabling the flexibility (plugin/out) for Industry 4.0 manufacturing network to work seamlessly. In this context, manufacturing organizations can connect devices with required data to perform business functions, enabling the maximum capacity of establishing instant business operation.

Advanced analytics: different domains/sources produce various data i.e., big data with different forms; hence it must be managed properly. New methods and advanced technologies supporting big data analytics, deep learning, etc., are however needed as traditional data processing methods and tools are unable to process such data. In this context, predictive model utilizing state-of-the-art techniques, instead of relying on model-based or experience-based methods which are ineffective as well as costly (Mobley, 2002).

We compiled some of the different aspect such as as issues, advantage, etc. regarding existing approaches from the related-work as presented in Table 2.3.

2.3 Predictive Model for Maintenance

Generally, various predictive models including wear detections (i.e., worn, failure, degradation) and remaining useful life (RUL) are used. The developed predictive models can be deployed for the prediction/detection of failure or degradation. Predictive models for maintenance along with related factory and maintenance information provide a basis for determining predictive maintenance activity and schedule plans (Sang et al., 2021*a*).

Remaining useful life (RUL) is being recognized as an effective predictive maintenance since it can effectively estimate the end of life of a machine component (Sateesh Babu et al., 2016; Si et al., 2011; Tobon-Mejia et al., 2012; Zheng et al., 2017). In this context, maintenance based on RUL predictions can facilitates better optimizations such as in time acquiring of resources e.g. spare parts, engineer, etc., ultimately effective maintenance scheduling. Particularly, cases with complex systems i.e. multiple machines components, are maintained, and associated costs are high, the accuracy i.e. high and medium may contribute to significant savings. Based on the predictive RUL and its corresponding horizon, performance indicators or parameters can be determined for predicting the failure time (Sang et al., 2021*a*).

2.3.1 Remaining Useful Life

For industrial maintenance management, prognostics and health management (PHM) is essentially important for reducing maintenance costs (Mobley, 2002). Prognostics failure is based on the prediction of the future health condition of a given component, sub-system, or system and its remaining useful life (RUL) (Mobley, 2002).

Failure prognostics is described as "estimation of the time to failure and the risk for one or more existing and future failure modes." (ISO13381-1, 2015). Other definitions have been proposed in the literature (Heng et al., 2009; Jardine et al., 2006; Muller et al., 2008; Provan, 2003; Wang et al., 2004).

All the reported definitions agree about a prediction step, and the estimation of the time before the failure. This time is called RUL in some works, Estimated Time To Failure (ETTF) in Tobon-Mejia et al. (2010), and in some publications (Lin and Makis, 2003; Sohn et al., 2003) it is defined as a probability that a machine or equipment tool operates without a breakdown up to a future time.

Due to its capability of determining the maintenance time, RUL prediction is a key component of PHM (Sang, Xu, de Vrieze, Bai and Pan, 2020; Tobon-Mejia et al., 2012). The RUL of a machine equipment tool can be realized as *"the time period between the present*

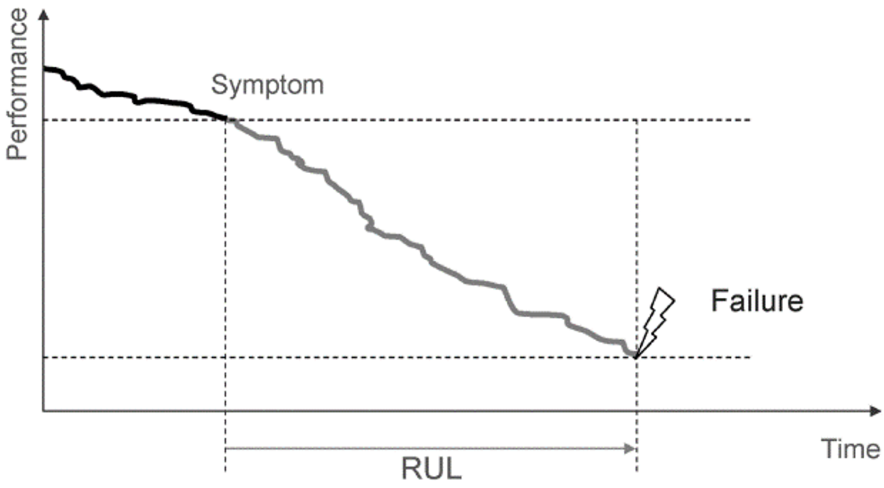


Fig. 2.11 RUL Illustration (Tobon-Mejia et al., 2012)

and the end of the useful life" (Sang, Xu, de Vrieze, Bai and Pan, 2020; Tobon-Mejia et al., 2012). An illustration of RUL is presented in Figure 2.11.

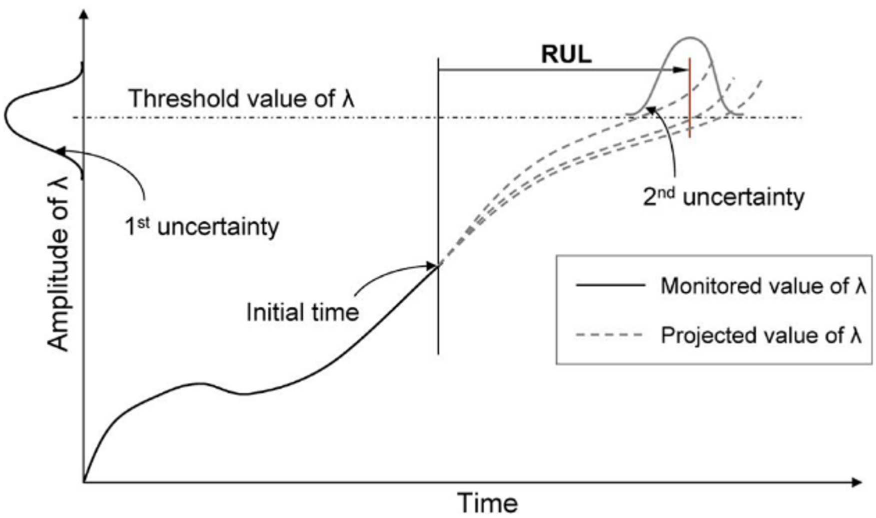


Fig. 2.12 The uncertainty related to RUL (Tobon-Mejia et al., 2012)

Several factors may impact the predicted value of the RUL (ISO13381-1, 2015). In the context of uncertainty related to RUL, a confidence interval may be considered for the aspect of uncertainty that is inherent to failure prognostics. In this way, a method for calculating the confidence value associated to a RUL prediction can be achieved (ISO13381-1, 2015). Figure 2.12 illustrates the RUL, and the associated confidence.

In this figure, there are two types of uncertainty: the first one relates to the prediction, and the second one is concerned with the threshold value corresponding to the complete breakdown of the machine (ISO13381-1, 2015). RUL is concerned with the aspect of prediction. RUL prognostics can be done in different approaches including model-based, experience-based and data-driven (Sang, Xu, de Vrieze, Bai and Pan, 2020; Tobon-Mejia et al., 2012).

2.3.2 Artificial Intelligence for Predictive Maintenance

Artificial Intelligence (AI) is a large field of research (Brewka, 1996). One of the most important branches of AI is machine learning (Brewka, 1996). It consists of many different techniques to predict or classify different data sources such as datasets, images, etc. There are two major groups of machine learning, namely supervised and un-supervised learning. In this research the focus is on the supervised learning (Brewka, 1996).

Supervised learning is a method where a function is created, which maps its inputs to a given output. This is based on a set of example input-output pairs. This consists of many different algorithms such as Random Forrest (RF), linear/logistic regression, neural networks and so on (Brewka, 1996; Goodfellow et al., 2016).

There are two techniques for building the models: regression and classification (Brewka, 1996; Goodfellow et al., 2016). For a classification model, the input is classified as one of the given "categories". This method can be used for image recognition, sound recognition or auto-correct functions. On the other hand, a regression method deals with coupling the input to a given number (float). A final value is given, which best represents the example input-output pairs (Goodfellow et al., 2016; Lei et al., 2018).

For the prediction of RUL of components, both techniques can be used. For classification approach, the health status of the machines/components are divided in a set of different health qualities (Lei et al., 2018). In the case of regression approach, it is to predict the number of time steps/cycles till failure will occur. For this research regression approach is chosen, since this allows for a better and more traceable prediction. In this way, maintenance can be planned, in advance and the status of the component can be checked on a regular basis. A classification model can suddenly switch from healthy to an unhealthy stage (Lei et al., 2018; Tobon-Mejia et al., 2012).

2.3.2.1 Neural Network (NN)

Neural networks was first introduced by McCulloch and Pitts (1943) as a way to model nervous activity. The characteristic of the neurons based on the “all or none”. In this context, the neuron has a certain threshold, and an impulse is initiated when the excitation exceeds the threshold. The impulse is then propagated across the neighbouring neurons. This is simply called a McCulloch-Pitts (MP) network (McCulloch and Pitts, 1943). This neural network inspires the modern neural networks that are created, with an input layer and an output layer. Rosenblatt (1958) introduces the concept of association cells which is comparable to the hidden layers used today. These association cells aim at learning features from images and recognise patterns (Goodfellow et al., 2016).

A neural network is based on a set of nodes i.e., neurons. These nodes are connected in a set of layers (Goodfellow et al., 2016). To create an input-output model, a signal is propagated across the connected different nodes. A certain weight is associated with each different connection. The weight is changed during training the network, and it determines the importance of the connected nodes i.e., the previous node to the next node.

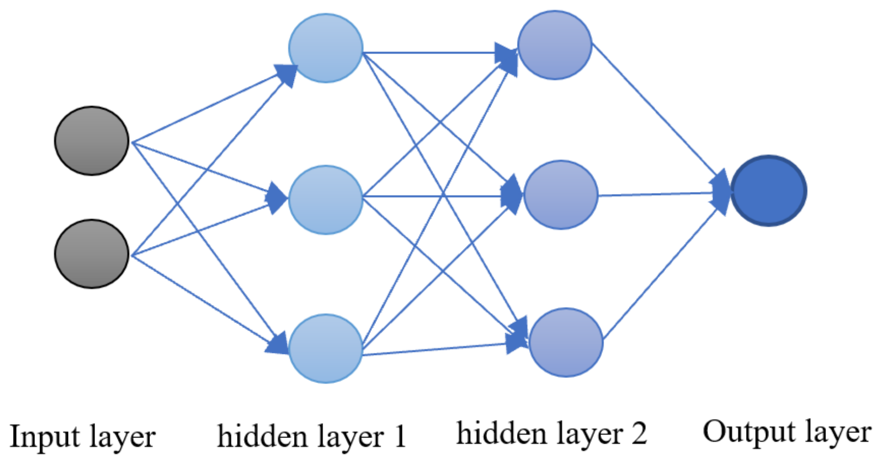


Fig. 2.13 A simple representation of a Neural Network. The layers are connected from the input to the output (Brewka, 1996).

Figure 2.13 illustrates an example of a neural network. The input layer is associated with a given input. Then the input is propagated across the connected layers. The output layer is the outcome of a single or multiple output values.

Figure 2.14 illustrates the mathematical notation of a neuron, where *a* represents the given activation (i.e. how the input is transferred to a given output) at layer *l* and the *jth* neuron. *w* and *b* represent the weights and the bias respectively. A bias is used to shift the activation and better fit the actual data. This needs to be performed across the previous layers to obtain the current activation value. *in* represents the sum over all previous layers.

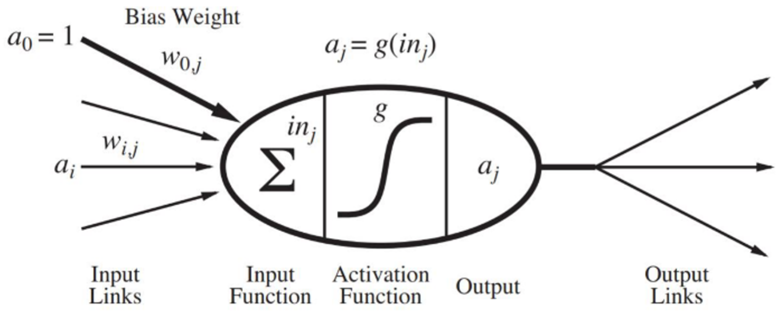


Fig. 2.14 A representation of the mathematical model of a neuron (Brewka, 1996)

2.3.2.2 Convolutional Neural Network

A Convolutional Neural Network (CNN) is often applied for models that deals with image and sound recognition (Brewka, 1996; Goodfellow et al., 2016). Usually, a filter known as kernel is used for a higher dimensional data. This filter can *highlight* and *specify* certain features in the high dimensional data, allowing different features selection (Brewka, 1996; Goodfellow et al., 2016).

CNN can be applied to for example, an edge detection kernel. The edges of the image in Figure 2.15 can be exaggerated. In this context, transferring the left image is first achieved in a 2D matrix, where all the pixels are represented as a number between 1 and 256. Then,Then, the data is processed with a specific value, applying a 3x3 kernel (Vincent and Folorunso, 2009). In this way, relevant information is highlighted and that leads to creating a higher accuracy for prediction.

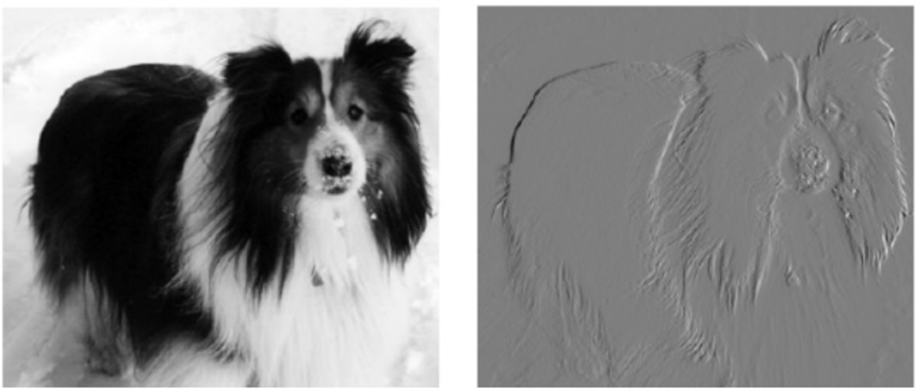


Fig. 2.15 Example of an Edge Detection (Brewka, 1996)

2.3.2.3 Long Short-term Memory (LSTM)

LSTM is a type of neural network known as a Recurrent Neural Network (RNN) (Hochreiter and Schmidhuber, 1997). It is an extended version of a standard RNN as RNN suffers from the vanishing gradient problem. LSTM then was designed to overcome the long memory problem, and thus is widely recognized for sequence or time-series learning problem (Goodfellow et al., 2016; Hochreiter and Schmidhuber, 1997).

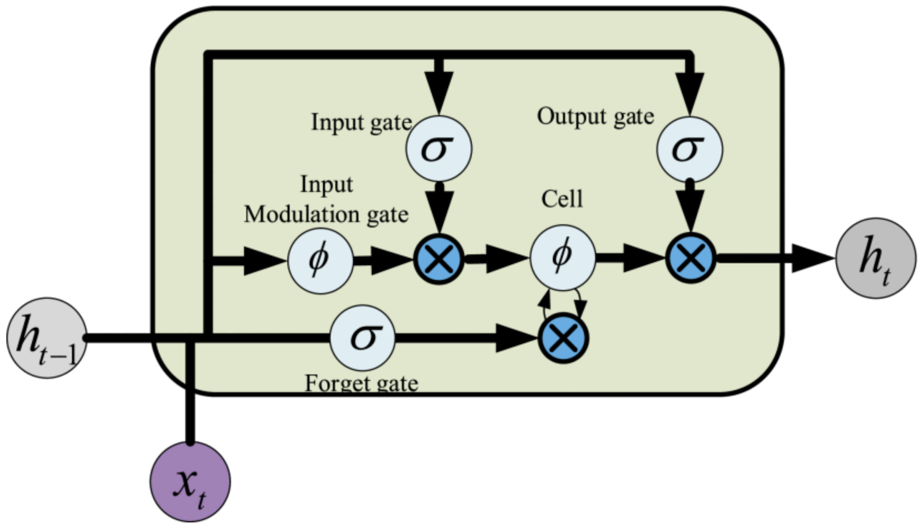


Fig. 2.16 LSTM Network Structure (Sak et al., 2014)

A LSTM cell contains three different gates: input, output and forget as illustrated in Figure 2.16 (Hochreiter and Schmidhuber, 1997). The amount of data in the cell is being controlled by each gate. The input gate deals with the incoming data whereas the forget gate deals with the data storage in the cell and the output gate computes the output of the activation (Hochreiter and Schmidhuber, 1997). In this context, the forget gate allows storing data over a larger number of epoch/updates, enabling predictions based on a sequence of input data (Hochreiter and Schmidhuber, 1997).

2.3.2.4 Develop Predictive Maintenance RUL Model

For RUL prognostics, predictive maintenance models can be constructed based on regression or classification (Sang et al., 2021*a*). A piece-wise linear (PWL) is used for RUL target function for a regression model (Zheng et al., 2017), and the accuracy result is generally based on the prediction horizon. On the other hand, the probability of the system RUL can be represented by different classes for a classification model. The probabilities of the system failure into different time intervals can be achieved (Sang et al., 2021*a*).

To demonstrate the concept, let's assume that sensors are deployed for monitoring equipment tools during factory operation. The monitoring data and the lifetime of each equipment tool are then used for building the model. To drive the learning of the model in the training stage, the sensor measurement sequences are taken as inputs by the predictive model e.g., LSTM. To determine RUL with each time window, the time step and the constructed LSTM model takes the sensor measurements as an input data and outputs the probable RUL (Sang et al., 2021*a*).

From multiple sources including sensors, data are collected and prepared for the input data (Sang et al., 2021*a*). These data however require pre-processing for training the model (Patro and Sahu, 2015). Such pre-processing can be achieved by performing normalization, data labeling, formalization, etc., based on the requirements of the model e.g., neural network (Patro and Sahu, 2015). Generally, it is necessary to normalize every feature value by its mean and variance, that leads to all features, being within the same range i.e. between zero and one (Goodfellow et al., 2016; Patro and Sahu, 2015; Sang et al., 2021*a*).

Data labelling, another task that is necessary for model training (Goodfellow et al., 2016; Patro and Sahu, 2015; Zheng et al., 2017). For RUL prognostics, data labelling can be processed based on the requirements of the operation engineers in which the time windows that the failure information required for e.g. maintenance and production activities. For example, a factory engineer may want information of system failure in different time windows. Using techniques such as piece-wise linear, data label then can be performed into two classes or time windows (Sang et al., 2021*a*).

Performance evaluation techniques depending on the learning methods i.e., confusion matrix for classification or Root Mean Square Error (RMSE) for regression can be utilized (Goodfellow et al., 2016; Zheng et al., 2017). RMSE is recognized as an effective evaluation method incorporating with a score function for measuring the quality of the models (Zheng et al., 2017). When the predicted RUL value is different i.e., smaller or larger to the true RUL value, RMSE gives the equal penalty weights to the model (Goodfellow et al., 2016; Zheng et al., 2017).

2.3.2.5 Dropout for overfitting problem

A neural network can be trained over a period of time. This however can risk of being overtrained. This refers to as overfitting (Srivastava et al., 2014). The overfitting problem occurs when the network has stopped finding patterns in the data (Srivastava et al., 2014). The network instead memorizes specific cases and thus lowers the generality of the network. And this makes it harder for the network to learn something new. To overcome or reduce the risk of this, dropout is often applied. Dropout works by controlling a certain percentage of nodes in the network, since these are chosen randomly (Srivastava et al., 2014). In this way, the network ensures all nodes are active. This risks of slowing down the training but increases the generalization of the network (Srivastava et al., 2014).

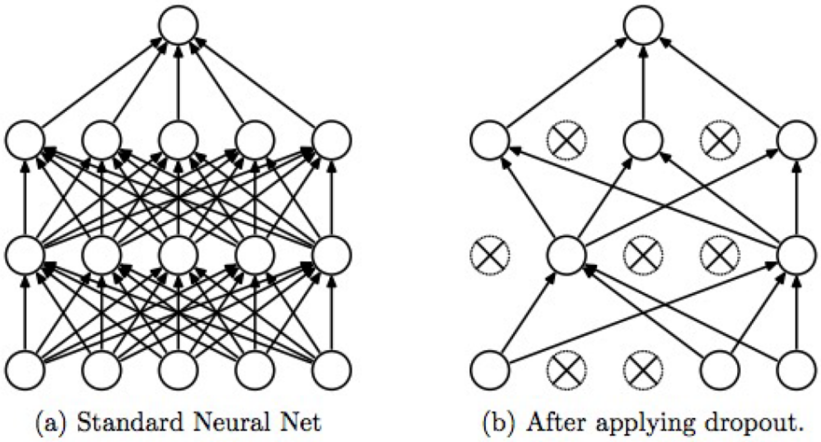


Fig. 2.17 An Illustration of Dropout (Srivastava et al., 2014)

2.3.2.6 Application of Artificial Intelligence for Remaining Useful Life

Prognostics and health management (PHM) assists in reducing maintenance costs in industrial maintenance management (Mobley, 2002). Due to its capability of determining the maintenance time, remaining useful life (RUL) prognostics is an essential function of PHM that has also attracted the interest of the research community (Mobley, 2002).

Prediction methods of sequence learning or time series are the focus of data-driven research for RUL prognostics due to the intrinsic nature of sequence or time series (Zheng et al., 2017). Several approaches based on analysis of sensor time series data and discovering relevant patterns associated with the prognostics task, have been proposed for RUL prognostic models (Srivastava and Mondal, 2016). These approaches offer an effective solution to the manufacturers (Mobley, 2002; Tobon-Mejia et al., 2012). The utilized techniques for prediction models include auto-regressive integrated moving average-based (ARIMA) models (Wu et al., 2007), hidden Markov models (HMM) (Baruah and Chinnam *, 2005), support vector regression (SVR) models (Benkedjouh et al., 2013), artificial neural networks (ANNs) (Arnaiz-González et al., 2016), random forest (RF) regression (Wu et al., 2017) and so on. These approaches deal with traditional dataset i.e., structured, and thus face challenges regarding big data i.e., complex, high frequency, and unstructured including streaming (Gers et al., 2000; Sang et al., 2017; Sang, Xu, de Vrieze and Bai, 2020*a*; Si et al., 2011).

As the data growth and complexity increase, the demand for advanced prediction methods arise as it is impossible for the traditional data processing and tools (Sang, Xu, de Vrieze, Bai and Pan, 2020). Deep learning has received great interest recently due to better RUL prognostics i.e. high prognostics accuracy, automatic feature extraction (Wang, Yu, Lai and Zhang, 2016). For RUL prediction, convolutional neural network (CNN) is widely utilized for dealing with sensor signals data for extracting high-level spatial features (Ren et al., 2018). Long short-term memory (LSTM) neural networks are specifically used for learning sequential sensor data (Zheng et al., 2017). A combination of CNN and LSTM was mainly used for natural language processing, speech processing, video processing (Ullah et al., 2018; Wang, Yu, Lai and Zhang, 2016; Zhao et al., 2017). And the addition of a health indicator in the learning data can lead to accurate prediction results (Lei et al., 2018). In this instance, utilizing additional feature may assist in learning the machine degradation.

2.3.3 Key Issues of Industry 4.0 Predictive Model for Maintenance

As the emergence of Industry 4.0 continues, many organizations face the challenges posed by the realities of AI implementation (Sang et al., 2021*a*). The benefits of predictive maintenance such as assisting determine the status of machine equipment tool and predicting when maintenance should be performed, are highly strategic. AI implementation may lead to significant cost savings, higher predictability, and increased availability of the systems (Mobley, 2002). This leads to engineers who put their efforts on the development of new technologies and techniques for facilitating the prediction of manufacturing equipment breakdowns and therefore to further optimize existing maintenance policies as well as to introduce more proactive maintenance policies (Mobley, 2002; Sang et al., 2021*a*). Predictive maintenance can be defined as a series of processes, where data is collected over time to monitor the state of machine equipment tool, in a manufacturing system. The goal is to discover patterns that in turn will facilitate engineers to predict and ultimately prevent failures (Sang, Xu, de Vrieze and Bai, 2020*a*).

Industry 4.0 manufacturing operates with several different systems, machines including robots, IoT devices, CNC machines, etc., and the nature of dynamic data can be extremely frequent and highly voluminous (Mobley, 2002; Sang et al., 2021*a*). Traditional methods such as auto-regressive integrated moving average-based (ARIMA) models (Wu et al., 2007), hidden Markov models (HMM) (Baruah and Chinnam *, 2005), support vector regression (SVR) models (Benkedjouh et al., 2013), artificial neural networks (ANNs) (Arnaiz-González et al., 2016), random forest (RF) regression (Wu et al., 2017), etc., are not efficient anymore. Thus, an approach that can deal with complex and high frequency data such as sensor time series/sequence, etc., collected from the factory production line, is required (Sang et al., 2021*a*).

Besides, multiple machines/components operated in the factory production of the Industry 4.0 manufacturing should be considered for the predictive model. Traditional manufacturing may involve specific factory machines which are normally maintained by the help of expert engineers, technicians utilizing model-based or experience-based approaches. These approaches are expensive as well as not effective in dealing with complex machines/components of Industry 4.0 (Sang et al., 2021*a*).

As the manufacturing is embracing the concept of Industry 4.0, factory operations and associated maintenance become difficult (Sang et al., 2021*b*) due to the dynamic nature i.e., business demands, complex systems, etc., and increasing collection and availability of big data. Predictive maintenance requires predictive models which can assist in managing an optimal maintenance (Sang et al., 2021*a*). This requires the continued optimization of predictive models with new collected data from factory operation considering sensor enabled multiple machines/components. Thus, the aspect of modularity and hybrid approach, the ability to adjust or update new business needs i.e., new data, new configuration of the model e.g., new network layer convolutional or LSTM, etc., is highly important for effective predictive maintenance.

We compiled some of the different aspect such as as issues, advantage, etc. regarding existing machine/deep learning methods for predictive maintenance model from the related-work as presented in Table 2.4.

2.4 Predictive Maintenance Schedule

Over time, the condition of the factory machines is hampered by the usage and age. This eventually leads to deficient operation or a machine failure if no maintenance action is taken (Mobley, 2002). Maintenance activities are hard and expensive (Mobley, 2002; Sang et al., 2021*a*). Ultimately the failures of the machine equipment tools impact the entire manufacturing network and may result in undesired downtime and costs (Sang et al., 2021*a*). Furthermore, the excessive or unnecessary maintenance caused by the machine failure can contribute to the overall maintenance downtime and cost (Mobley, 2002).

To avoid risks of failure or breakdown, maintenance activities such as preventive or predictive can be carried out (Mobley, 2002). Generally, preventive tasks are realized periodically. These tasks are planned for each machine. They require that machine should be stopped. Then, a scheduling problem appears when factory operations i.e., production tasks are also forecast. Since maintenance must be on time, constraints such as maintenance

Table 2.4 A summary of existing machine/deep learning for predictive maintenance model

Type	Typical Application	Advantage	Challenge
Traditional machine learing based			
Decision Tree, Random Forest, ARIMA (Si et al., 2011; Srivastava and Mondal, 2016; Tobon-Mejia et al., 2012; Wu et al., 2007)	Fault diagnosis	Easy to understand	Easy to over-fit
	Fault prognosis	Non-parametric	Poor prediction accuracy Unstable
SVM (Benkedjouh et al., 2013; Santos et al., 2015; Si et al., 2011)	Fault diagnosis	Work well with even un-structured and semi structured data	No probabilistic explanation for the classification
	RUL prediction	Can deal with high dimensional features	No standard for choosing the kernel function
		The risk of over-fitting is less	Low efficiency for big data
HMM (Baruah and Chinnam *, 2005; Si et al., 2011; Tobon-Mejia et al., 2012)	Fault diagnosis	Work well with even un-structured and semi structured data	No probabilistic explanation for the classification
	RUL prediction	Can deal with high dimensional features	No standard for choosing the kernel function
		The risk of over-fitting is less	Low efficiency for big data
Deep Learning based, efficiency for big data			
Autoencoder (Chen and Li, 2017; Ma et al., 2018)	Feature extraction	No prior data knowledge needed	Needs a lot of data for pre-training
	Multi-sensory data fusion	Can fuse multi-sensory data and compress data	Cannot determine what in-formation is relevant
		Easy to combine with classification or regression methods	Not so efficient in reconstructing
RNN (Goodfellow et al., 2016; Wang, Zhuang, Duan and Cheng, 2016)	Fault diagnosis	Model time sequential dependencies	Gradient vanishing and exploding problems
	RUL prediction		Cannot process very long sequences if using tanh or relu as an activation function
	Health indicator construction		
CNN (Goodfellow et al., 2016; Sateesh Babu et al., 2016; Wang, Yu, Lai and Zhang, 2016)	Fault diagnosis	Outperforms ANN on many tasks (e.g., image recognition)	Hyperparameter tuning is nontrivial
	RUL prediction	Would be less complex and saves memory compared to the ANN	Easy to over-fit
		Automatically detects the important features without any human supervision	High computational cost
			Needs a massive amount of training data
LSTM (Goodfellow et al., 2016; Wang, Yu, Lai and Zhang, 2016; Zheng et al., 2017)	Fault diagnosis	Model time sequential dependencies	High computational cost
	RUL prediction		Can be long process if different layers are used
	Health indicator construction		
DRL (Brewka, 1996; Chen et al., 2021; Rocchetta et al., 2019)	Operation and maintenance decision making	Can be used to solve very complex problems	Needs a lot of data and a lot of computation
	Fault diagnosis	Maintains a balance between exploration and exploitation	Assumes the world is Markovian, which it is not
	Health indicator learning		Suffers from the curse of dimensionality

machines/components, factory production scheduling, etc., are considered. Besides, preventive approach is relied on static or regular plan and it is not optimized in dealing with complex and dynamic nature of Industry 4.0. On the other hand, predictive maintenance based on data-driven prediction of failure offers maintenance management in a more effective way (Mobley, 2002; Sang, Xu, de Vrieze and Bai, 2020*a*).

The problem of scheduling in manufacturing has attracted the interest of many research communities including management science, industrial engineering, operations research (OR) and artificial intelligence (AI). The emergence of Industry 4.0 and advanced technology, the increasing complexity of manufacturing systems, processes and dynamic demands drive the organizations to manage their operations in an optimized and efficient manner (Sang et al., 2021*a*).

2.4.1 Manufacturing Scheduling

A typical scheduling system is illustrated in Figure 2.18. It consists of all data, libraries, algorithms, editor, and evaluation as well as user interacting via graphics interface (Pinedo, 2016). Data are collected from different systems into database system. All data are then fed into the schedule generator which utilizes algorithms and libraries to produce a schedule which is accessible via the schedule editor (Pinedo, 2016; Sang et al., 2021*a*). Result of the schedule generator can be then accessible by the user via a user interface.

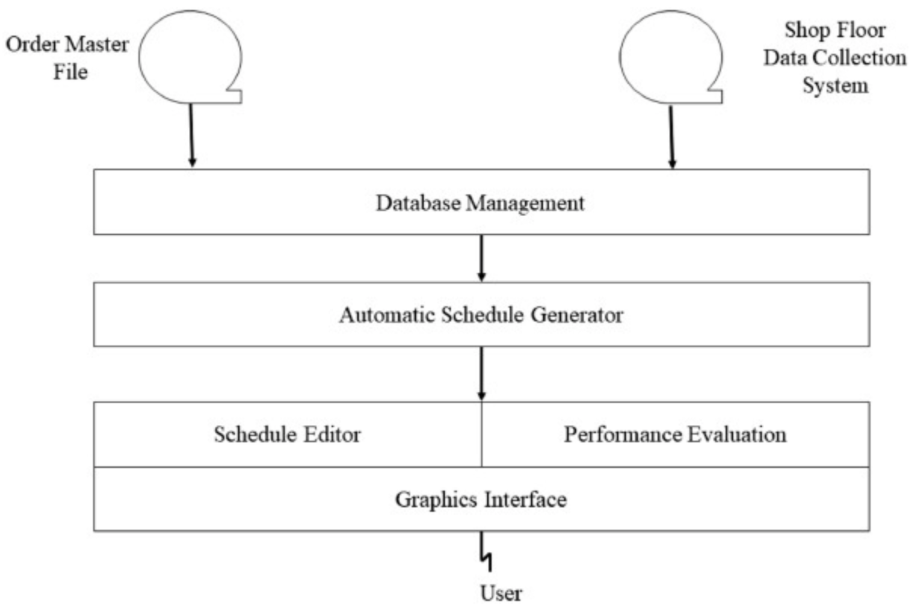


Fig. 2.18 Scheduling System (Pinedo, 2016)

Manufacturing scheduling can be described as "an optimization process that assigns limited manufacturing resources over time among parallel and sequential manufacturing activities" (Pinedo, 2016). The process operates with a set of constraints that reflect on the capacity limitations of a set of shared resources and related activities. The optimality of a schedule with respect to different criteria is also constrained by the process (Pinedo, 2016).

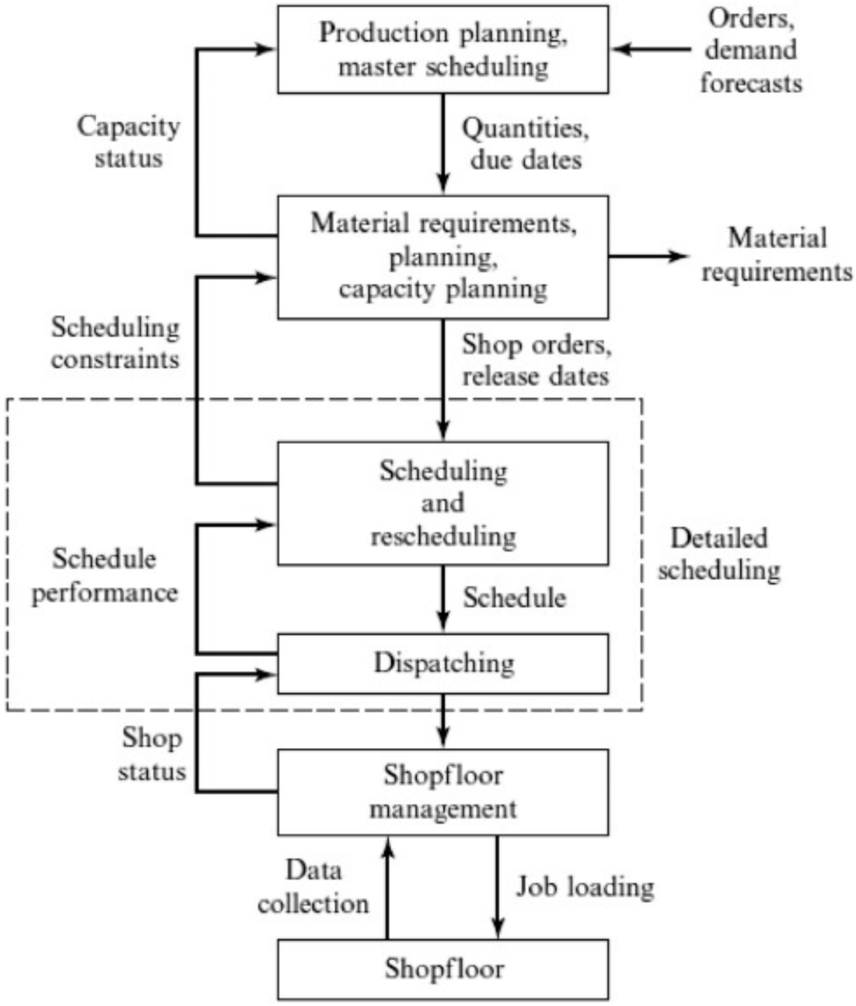


Fig. 2.19 Production Planning and Control scheme (Pinedo, 2016)

Figure 2.19 is a typical illustration of the information flow in a manufacturing/production system. In general, in a manufacturing system, the scheduling and other functions interact for decision-making process (Pinedo, 2016). The scheduling lies in the middle section that determines the different important factors such as the stock levels, the demand forecasting, and the requirements plan, for the optimization of the allocation of resources. The support of an advanced decision support tool is ideal for the construction of a feasible and optimized schedule plan (Pinedo, 2016). Without the support tool, the schedule plan can be a very difficult and time-consuming procedure that requires not only deep knowledge of all the data and parameters of the production system, but also specific knowledge in specific field (Pinedo, 2016).

2.4.1.1 ANSI/ISA 95

A high level of the manufacturing scheduling system which considers the previously described functionalities can be presented by ANSI/ISA 95 standard. It is a widely accepted representation of the architecture of an organization and its different levels of decision-making (Rossit and Tohmé, 2018).

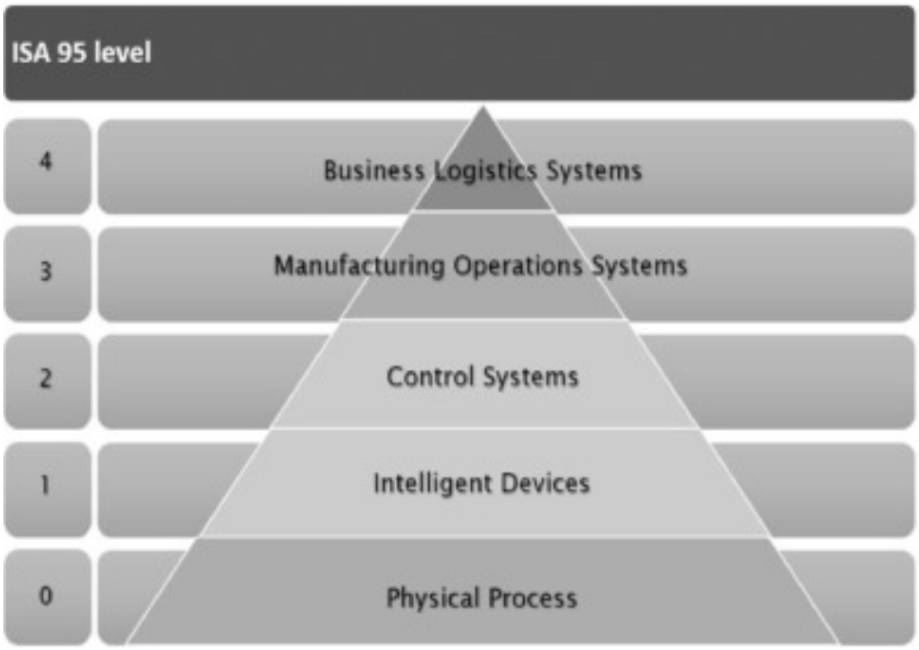


Fig. 2.20 Structure of ANSI/ISA 95 (Rossit and Tohmé, 2018)

The ANSI/ISA 95 may serve as a framework for an interface between the production facilities and control systems (Rossit and Tohmé, 2018). ANSI/ISA 95 can act as a bridge for all participants in a production process for providing a representation of how information that can be modelled and used (Rossit and Tohmé, 2018). It facilitates the organization of the different levels of decision-making hierarchically. As depicted in Figure 2.20, the different levels can be classified into five levels:

- Level 0 is concerned with the physical process of manufacturing.
- Level 1 presents the smart devices i.e., sensors, etc., that measure and manipulate the physical process.

- Level 2 represents the control and supervision of the underlying activities. This includes Supervisory Control and Data Acquisition (SCADA), Programmable Logic Controllers (PLC) etc.
- Level 3 involves the management of the operations and the production workflow in the production of the desired products. This includes Management, manufacturing execution/operations management systems (MES/MOMS), maintenance and plant performance management systems, data historians and related middleware, etc. And it is here where the scheduling process takes place.
- Level 4 is concerned with the business activities of the entire organization. It represents, in a synthetic way, the different activities and functions of a production system. Besides, it establishes the way in which the different levels communicate; in traditional productions settings, in particular each level interacts only with its adjacent levels.

The described manufacturing scheduling in Figure 2.18, Figure 2.19 and ANSI/ISA 95 in Figure 2.20 explain the overall aspect of the manufacturing scheduling, particularly production. Maintenance scheduling, which is part of the manufacturing scheduling as illustrated in Figure 2.18 and Figure 2.20 (i.e. level 3 of ANSI/ISA 95) can be considered as the same process since similar information systems such as ERP, MES, etc., including information of maintenance, machine equipment tools, etc., as well as other constraints e.g., capacity, material, etc., are required for the scheduling.

2.4.2 Maintenance Scheduling

Maintenance scheduling is part of the manufacturing scheduling systems described in ANSI/ISA 95 i.e. level 3 as well as in Figure 2.18 and Figure 2.20. Like the production scheduling, data related to manufacturing production and systems, algorithms, etc. are required for maintenance scheduling.

Generally, scheduling problems including maintenance activities can be described by two common approaches, one with constraints or with coordinated approach. The one with constraints focus on pre-defined or fixed constraints including times including start and end of the activity, duration of the activity. On the other hand, the coordinated approach focuses on the overall process of conducting the maintenance activity and job simultaneously (Pinedo, 2016).

The maintenance objective is proposing the optimal schedule plan for the machines that are required for maintenance while optimizing the availability of machines (Sang et al., 2021*a*). The regular interval or periodicity of preventive maintenance limits the risk of breakdown. The cost of maintenance then will increase if preventive maintenance is delayed since the risk of failures increases (Sang et al., 2021*a*). Then, the objective for maintenance plan is to be on time. early maintenance task will increase the cost of maintenance and late task will lead to unexpected cost for reactive maintenance (Sang et al., 2021*a*).

Current maintenance scheduling approaches are mostly based on conventional maintenance approaches such as reactive or preventive mostly rely on either model-based or experience-based approach which is based on domain experts or failure events (Sang et al., 2021*a*; Sang, Xu, de Vrieze and Bai, 2020*a*). Maintenance schedule is performed based on regular routine, pre-determined or immediate or deferred i.e. reactive maintenance. Thus, they are expensive as well as it is impossible to manage the increasing complex nature of Industry 4.0 focusing manufacturing systems which operate with different multiple machine equipment tools (Sang, Xu, de Vrieze and Bai, 2020*b*).

2.4.2.1 Predictive Maintenance Scheduling for Industry 4.0

Predictive maintenance scheduling for Industry 4.0 is facilitated by predictive models, related factory and maintenance information. Using historical machine data, i.e., operation and condition, predictive models are built. Advanced capabilities such as big data analytics incorporating predictive models enables predictive maintenance to being able to the advanced detection of potential failures and timely pre-failure interventions. This leads to offering an effective way of managing maintenance and the capability of prescriptive maintenance (Sang et al., 2021*a*).

Unlike traditional manufacturing systems (e.g. a system can be independent), Industry 4.0 driven manufacturing systems are complex systems of strongly interconnected machines or devices who interact and collaborate for business processes towards common goals (Almada-Lobo, 2016; Sang, Xu, de Vrieze and Bai, 2020*b*; Thoben et al., 2017). As such, predictive maintenance scheduling should consider the dependencies of various machine components involved. Thus, a concrete strategy that can efficiently coordinates the failure prediction and maintenance schedule, to ensure optimized operation and productivity, is critically important.

For traditional manufacturing scheduling, Manufacturing Execution Systems (MES) are often used (Pinedo, 2016). However, Industry 4.0 manufacturing systems are complex and thus, the demands of increased flexibility and scalability in dealing with such diverse systems cannot be met by MES. As manufacturing paradigms are adopting the concept of Industry 4.0, a new approach that is flexible to support managing the manufacturing processes (e.g. maintenance) efficiently, is needed (Sang et al., 2021*a*).

Industry 4.0 operates with many several systems and machine equipment tools (Sang et al., 2021*a*; Zezulka et al., 2016). Thus, predictive maintenance scheduling must consider the aspect of complex systems i.e. multiple machines components (Sang et al., 2021*a*). The cost of separate maintenance for each of the multiple machine components at different times is highly expensive. For example, the resource availability of each machine component, the type of each maintenance, i.e., repair or replacement, and the setup cost of each maintenance, i.e., shutdown and up, can be time-consuming and costly (Sang et al., 2021*a*). Thus, considering the resources while coordinating potential pending failures within a time window is much desired (Sang et al., 2021*a*). Different aspect of maintenance scheduling optimization is described in the next section.

2.4.3 Maintenance Scheduling Optimization Approaches

Maintenance scheduling optimization can be described as "to determine effective and efficient maintenance plans for each component of a system to meet operator requirements for safety, reliability, and value" (Do et al., 2019). In this study, we describe maintenance scheduling optimization as the process of scheduling optimization by considering the multiple machines/components with related constraints such as maintenance resource, availability and cost, driven by predictive model and related information i.e. maintenance, machine, production, etc., that produces optimal plans facilitating effective maintenance decision making.

Maintenance scheduling optimization can be done to either single or multiple machines/components using the required capacities and costs (Framinan and Ruiz, 2010; Mobley, 2002; Nicolai and Dekker, 2008; Pinedo, 2016; Sang et al., 2021*a*; Sang, Xu, de Vrieze and Bai, 2020*b*). In this study, the focus is on multiple machines/components to better deal with Industry 4.0 focusing factory context. It should also be recognized that the optimization of multiple machines/components may be applied to single machine/component machine scheduling.

In the context of traditional maintenance optimization approach, different dependencies such as structural, economic, stochastic, etc. are described. Regarding structural dependence refers to the structural, static relationships between different components of a machine . In the context of maintenance, structural dependence is considered for a case where the replacement of a certain component requires the replacement of other components, the case in which a component is stopped due to failure or maintenance of another component. Maintenance (i.e., reactive or preventive) is based on the model driven by the structure of the different components associated with a machine, and maintenance can be costly.

To optimize the aspect of maintenance cost, economic dependence (or opportunistic for grouping) is introduced by Dekker et al. (1997*a*). In this context, utilizing model driven by structure dependence, the maintenance of different components is grouped for saving maintenance cost. This approach can make huge impact on cost saving when maintenance is associated with high costs (e.g., multiple engineers required for several tasks, production downtime due to several maintenance activities, etc.,). On the other hand, maintaining several components simultaneously may lead to higher costs than maintaining them separately due to different constraints such as production losses, safety requirements, or systems with restrictions such downtime, engineer, etc.

The deterioration or failure process of a machine component can also impact the other components operating in production. This approach is described as stochastic dependence by Van Horenbeek and Pintelon (2013). If a component fails, the system keeps operating but the remaining components structurally need to work harder to realize the same output level. Essentially, the failure or inefficient process of a machine component may cause damage to other components, leading to an increase of the deterioration level or even an instant failure of these components. At this stage, the aspect of structural, economic, and stochastic dependence generally focuses on model driven approach whereas the physical degradation of the machine component or domain experts is utilized, and maintenance schedule plan is mostly intended for reactive or preventive (i.e., regular, planned, routine) activities.

Industry 4.0 manufacturing utilizes complex systems including various linked systems and machine equipment tools e.g. CPS, IoT, robots, CNC machines and thus maintenance is challenging. Single-component systems are predominantly studied for traditional maintenance (Chan and Asgarpoor, 2006; Wang, 2002). In this instance, a single machine or component is only considered for maintenance and thus the related machines/components are overlooked. Maintenance of multi-component systems thus becomes the focus of various works (Dekker et al., 1997*a*,*b*; Van Horenbeek and Pintelon, 2013). In these works, the consideration of a machine with more than one component is included for maintenance. To optimize the aspect of multi-component maintenance, consideration such as economic i.e., cost related to downtime, machine, is presented by Dekker et al. (1997*a*) for cost savings. Mourtzis et al. (2017) present an integrated system, under the concept of Industry 4.0. The approach focuses on the availability of timeslot for maintenance schedule which is facilitated by the data gathered from the monitored equipment. Senra et al. (2017) put forward a schedule process that is based on available equipment with support technicians as well as related processing times. They illustrated the approach using a case study. The approach however lacks the aspect of equipment monitoring for analytics. For production maintenance synchronization, (Levrat et al., 2008) present a decision-making tool. It is based on multiple criteria such as product performance and component reliability for producing an optimal scheduling plan. For job shop scheduling, ZHENG et al. (2013) present a scheduling method that incorporates a condition-based maintenance for producing an optimal solution.

Based on existing approaches, it is clear that there is an opportunity for a new approach that considers data-driven predictive models in the context of Industry 4.0, particularly the applicability of different types of machines and the overall schedule for producing optimal maintenance schedule for complex manufacturing.

2.4.4 Key Issues of Industry 4.0 Predictive Maintenance Schedule

As shown in the discussion regarding the emergence of Industry 4.0, the complexity of machine equipment involved in modern collaborative industry has rapidly increased (Sang et al., 2021*a*). Any failure of machine equipment tool may have significant impacts, and maintenance is key for operating the machine equipment effectively (Mobley, 2002). Therefore, it is essential to have an effective strategy that efficiently coordinates the failure prediction or detection and maintenance scheduling to ensure the optimized operation and productivity (Sang et al., 2021*a*). A summary of the key issues related to Industry 4.0 predictive maintenance schedule is compiled as below:

2.4.4.1 Consideration of multiple machines/components

Predictive maintenance schedule requires the consideration of multiple machine components i.e., different systems/components e.g. IoT devices, CNC machines, tools, etc. operating in Industry 4.0 collaborative manufacturing. Currently, different aspects of maintenance such as single-component (Chan and Asgarpoor, 2006; Wang, 2002) and multi-component (Dekker et al., 1997*a*,*b*; Van Horenbeek and Pintelon, 2013) systems are predominantly explored in the research community. These studies mostly relied on traditional monolithic manufacturing context, the physical structure of the machine component, expert knowledge for both reactive and preventive maintenances, and most importantly they failed to address the consideration of data-driven approach with multiple machine components in the context of multiple organizations/manufacturing factories in collaborative Industry 4.0 setting.

2.4.4.2 Complex factory operation and production

In the case of multiple machine components, different machine components are interconnected or linked in a factory operation context. For a production line, a machine might have different dependencies or components as well as a combination of different components are often integrated for operation. For the maintenance activity or task, it may be either repair or replacement of an entire machine or a component. Traditional approaches that utilize systems such as MES cannot meet the demands of complex Industry 4.0 focusing manufacturing (Pinedo, 2016; Sang et al., 2021*a*). Advanced capabilities such as big data analytics, deep learning, etc. are required in dealing with big data i.e., sensor data, predictive analytics, etc., accumulation of information across the many different systems, machines., etc., for assisting maintenance (Mobley, 2002; Pinedo, 2016; Sang et al., 2021*a*).

2.4.4.3 Maintenance resource, cost, and availability

The associated downtime and cost of maintenance, especially in Industry 4.0 manufacturing can be huge (Deloitte, n.d.; Sang et al., 2021*a*). Existing approaches such as structural, stochastic, etc., rely on model-based or experience-based methods which are costly, ineffective as well as do not consider the aspect of Industry 4.0 (Sang et al. 2021a). In a factory context, the availability refers to the time when the maintenance activity of the machines/components is intended to perform. The cost directly associates with the maintenance task, time, and availability as well as the cost incurred to downtime within a collaborative context. To minimize downtime and cost, the different aspect of maintenance such as resource i.e., engineer, tools, spare, etc., their availability and associated cost should be considered for an optimal predictive maintenance scheduling (Sang et al., 2021*a*).

2.4.4.4 Dynamic procedure

Managing the demands of highly collaborative complex systems of Industry 4.0 focusing manufacturing is challenging (Sang, Xu, de Vrieze and Bai, 2020*a*; Thoben et al., 2017). In the context of predictive maintenance scheduling, several considered parameters are involved as described in Section 2.4.3. Thus, efficiency is of important. Predictive maintenance scheduling thus should be considered as dynamic, when different parameters can be adapted to different demands. For example, different RUL of a machine component or all can be regarded as an input parameter for a business reason e.g. different time windows may need to be considered for potentially not fulfilling orders, etc.

2.4.4.5 Complex collaborative network

In an Industry 4.0 collaborative network context, each participant firm has its specialized expertise and offers its service to the network (Sang et al., 2021*b*). In this context, a factory with predictive maintenance can offer the capability i.e. predictive maintenance as service to the network. From a predictive maintenance service provider aspect, different machines need to be monitored in multiple organizations within a collaborative network factor. When scheduling a predictive maintenance plan, the predictive maintenance services can be planned as efficiently as possible, for example, the organizations geographical closed may schedule

Table 2.5 Summary of existing maintenance scheduling approaches

Approach	Short Description	Data-driven/Predictive	Consider for integrated Predictive Maintenance Platform/Solution
Single Machine Component (Chan and Asgarpoor, 2006; Liu et al., 2013; Wang, 2002)	Focus on single machine component for maintenance modeling, mostly preventive maintenance	No, mostly modelling/ mathematical	No, traditional stand-alone
Sing Machine with multiple Component or Multiple Components (Camci, 2009; Dekker et al., 1997*a*,*b*; Van Horenbeek and Pintelon, 2013)	Focus on single machine with multiple component or multiple component with cost saving, specifically downtime related cost and for preventive maintenance	No, mostly modelling/ mathematical	No, traditional stand-alone
An integrated system with equipment schedule (Mourtzis et al., 2017)	Focus on a specific monitored equipment and adjust schedule upon timeslot availability	Yes, no predictive maintenance	Part of a system, only considered for schedule
Equipment schedule process (Senra et al., 2017)	Consider available equipment with support technicians, as well as the related processing times for the schedule process	Yes, no predictive maintenance	Part of a system, only considered for schedule
Failure patterns detected by a BDA procedure in databases the system (Ji and Wang, 2017)	Consider specific equipment for predictive maintenance based on knowledge-based database	Yes, predictive maintenance	Mainly focus on predictive maintenance, lack of consideration for schedule
Online predictive maintenance and continuous quality control (Lindström et al., 2017)	Consider equipment tool (specified) for predictive maintenance for control process	Yes, predictive maintenance	Mainly focus on predictive maintenance, lack of consideration for schedule
Continuous-time predictive-maintenance for a deteriorating system (Grall et al., 2002)	Based on decision model and model-based for single-unit system maintenance process	Yes, predictive maintenance	Mainly focus on model-based (degradation), lack of consideration for schedule

closer to save time, the similar machines in different organizations which similar conditions may change components at the same period to save costs, etc.

We compiled some of the different aspect such as as issues, advantage, etc. regarding existing methods for predictive maintenance scheduling from the related-work as presented in Table 2.5.

2.5 Summary of related work and requirements for Industry 4.0 Predictive Maintenance

As the discussions have shown, Industry 4.0 and predictive maintenance relates to various aspects considered under different concepts of Industry 4.0: architecture, predictive maintenance, predictive model, and maintenance schedule optimization for decision making. We described the different concepts and some of their key issues related to Industry 4.0 identified in existing work. In Section 2.1, we discuss the general concept of maintenance and a need of predictive maintenance in dealing with Industry 4.0 focusing manufacturing environment. Some of the key issues related to predictive maintenance for Industry 4.0 are summarized in Section 2.1.4. Industry 4.0 and related concepts are described in Section 2.2. Architecture model and its implementation platform regarding predictive maintenance in the context of Industry 4.0 are discussed and some key related issues are presented in Section 2.2.5. Predictive maintenance is facilitated by predictive model which drives the maintenance schedule plan for decision making (Sang et al., 2021*a*). Predictive model for maintenance is discussed, and some key issues related to predictive maintenance in the context of Industry 4.0 are presented in Section 2.3.3. Utilizing the predictive model, predictive maintenance schedule is discussed in Section 2.4. A need for Industry 4.0 predictive maintenance schedule supported by optimization, identifying some key issues, are presented in Section 2.4.4.

We have noted that the issues and requirements of Industry 4.0 predictive maintenance scales beyond the requirements for traditional maintenance systems and processes due to the unique characteristics of these processes. Based on the discussion and analysis of related work, the key issues and gaps identified formed propositions to the requirements necessary for a new approach for Industry 4.0 predictive maintenance. In addition to the key issues' discussion provided in Section 2.1.4, Section 2.2.5, Section 2.3.3 and Section 2.4.4, we also have complied some of the different aspect such as as issues, advantage, etc. regarding maintenance, architecture model, predictive model and maintenance scheduling from the related-work in Table 2.1, Table 2.3, Table 2.4 and Table 2.5 that form some of the key requirements. A summary of the key issues and requirements are presented below:

2.5.1 Key issue 1 and related requirement

Flexible architecture platform for Industry 4.0 predictive maintenance is essentially important for Industry 4.0 focusing manufacturing network. Since Industry 4.0 represents the value-creating network established by the utilization of emerging advanced technologies such as Internet of things, Cyber Physical Systems, etc. In this context, the factory plants and machines are empowered with the ability to adapt their operations and operating conditions such as reconfiguration using advanced capabilities such as big data analytics (Sang, Xu, de Vrieze and Bai, 2020*a*). Essentially, the fundamental business processes are facilitated by the several components which interact and exchange data (Sang, Xu, de Vrieze and Bai, 2020*a*). The complexity of these various systems, processes, etc., can be easily understood and flexible enough to support business dynamic needs i.e., optimization of different machine equipment tools utilizing advanced capabilities to support maintenance services and decision making. Thus, an architecture model that supports *flexibility* is a highly important requirement.

2.5.2 Key issue 2 and related requirement

Interoperability for the integration of different systems, processes, machine equipment tools operate in an Industry 4.0 environment. Many different manufacturing domains encompass a wide variety of systems where each of them has their own formats, concepts, relationships, data structures, syntaxes, and semantics. This brings in complexity and limits interoperability across domains. While they may perform flawlessly within their standalone applications, they do not fare well when there is a need to share knowledge. This identifies the need to address interoperability problems and more specifically minimize the semantic mismatches. For predictive maintenance, interoperability i.e., the ease integration of the existing machines, robots, systems, etc. and predictive maintenance can be easily achieved. Thus, *interoperability* is one key *requirement* that should be considered for Industry 4.0 predictive maintenance.

2.5.3 Key issue 3 and related requirement

Supporting *Modularity* for efficient maintenance operation which is required for dealing with the dynamic nature and demands of complex Industry 4.0 manufacturing network (Hribernik et al., 2018; Koren et al., 2018). Since, many different systems, machines, tools, and processes operate in an Industry 4.0 environment, different capabilities supporting maintenance services are needed to be integrated for predictive maintenance in collaborative manufacturing. The embedded predictive maintenance services into the existing systems can easily be adapted to different needs or can be integrated with different system processes without significant engineering effort and cost. *Modularity* is the basis for Industry 4.0 manufacturing systems and that the features of modularity meet the dynamic demands and integrations in Industry 4.0 (Sang, Xu, de Vrieze, Bai and Pan, 2020).

2.5.4 Key issue 4 and related requirement

Implementation platform or framework of flexible architecture model is important for providing a consistent predictive maintenance system, particularly for complex Industry 4.0 manufacturing. Architecture models such as RAMI 4.0, 5C and IIRA, focus only on the architecture design regarding understanding of complex systems, processes, etc., and do not consider the aspect of implementation platform or framework which supports Industry 4.0 standards and modularity. In increasing complex Industry 4.0 manufacturing environment, there exist different adapters for data interaction from different levels, i.e. components, machines, systems, as well as data from collaborative partners, suppliers and customers. These collaborative interactions normally are dealt with different data models for each own requirement which do not normally consider for interoperability or modularity (Sang, Xu, de Vrieze, Bai and Pan, 2020). For instance, smart systems such as CPS, CNC, or robot, has its own data interface which might not be straightforward to integrate with the monitoring system for predictive maintenance. A flexible architecture platform should allow using of pre-defined modules of well-known data standards as well as supports to extend new adapters to access different types of or new data standards. And this leads to 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 (Sang, Xu, de Vrieze, Bai and Pan, 2020). The *modular architecture platform* should facilitate the easy integration of different components as pluggable elements, without significant engineering effort or cost (Sang, Xu, de Vrieze, Bai and Pan, 2020).

2.5.5 Key issue 5 and related requirement

Advanced maintenance capabilities as discussed in Section 2.1, existing approaches such as model-based or experience-based are based on domain experts or the physical structure and degradation of the machine tools. Besides, maintenance activities are based on reactive or preventive maintenance approaches which only deal with reacting the failure of the machine tools (i.e, reactive) or regular or routine maintenance for the preventive. Thus, these approaches are time-consuming as well as costly. Particularly, those approaches do not consider for the complex systems involved in the context of Industry 4.0 as well as it is impossible to deal with the multiple machines/components operating in factory production. Thus, data-driven predictive maintenance utilizing the various data collected from factory machine equipment tools, systems, and processes is an important requirement for Industry 4.0 predictive maintenance.

Specifically, two key components i.e., predictive model for maintenance, maintenance schedule driven by predictive maintenance model for decision making and schedule plan, of data-driven predictive maintenance are essential to supporting Industry 4.0 predictive maintenance (Sang et al., 2021*a*). Thus, the two key requirements i.e., *Key issue 6 and Key issue 7* can be further described, to better support data-driven predictive maintenance.

2.5.6 Key issue 6 and related requirement

Modular predictive model for Industry 4.0 predictive maintenance as discussed in Section 2.3, existing methods such as HMM, RNN, etc., as well as traditional data processing and tools are not effective in dealing with sensor data (Sang et al., 2017; Sang, Xu, de Vrieze, Bai and Pan, 2020). Data-driven predictive maintenance model based on state-of-the-art should be considered in dealing with complex systems involved in the Industry 4.0 systems as well as high frequency and complex data such as sensor/sequence data collected from systems and machine equipment tools of manufacturing factory. To better support the dynamic needs of Industry 4.0 and complex systems i.e., machines/components, predictive maintenance model should support different capabilities such as hybrid as well as the ability to change or configure the model in a modular manner.

2.5.7 Key issue 6 and related requirement

Predictive maintenance scheduling as described in Section 2.4, existing approaches focus on traditional methods based on model-based or experience-based which still ignore the aspect of Industry 4.0. Thus, data-driven predictive maintenance schedule should consider for multiple machines/components, maintenance resource, cost and availability with dynamic feature i.e. modularity. Based on the characteristics of collaborative Industry 4.0 focusing manufacturing and existing literature studies, several critical factors such as multiple machines, cost, time, availability, are identified and cooperated with the proposed maintenance process.

2.6 Chapter Summary

This chapter discussed the concept of Industry 4.0 and predictive maintenance including key issues that form related requirements, as a basis for flexible architecture platform, . The related work demonstrates Industry 4.0 predictive maintenance as related field who research is vast and still growing in differing dimensions. We explored the different concepts and related work of Industry 4.0 predictive maintenance including predictive maintenance for Industry 4.0 and related key components such as predictive maintenance model, and predictive maintenance schedule. Some of the key issues related to the described concepts i.e., predictive maintenance, architecture model and implementation platform or framework and advanced capabilities such as big data analytics, deep learning approach and predictive maintenance scheduling in the context of Industry 4.0 predictive maintenance are discussed and identified.

We have discussed the key issues and related requirements previously in Section 2.5, and complied some of the different aspect such as as issues, advantage, etc. regarding maintenance, architecture model, predictive model and maintenance scheduling from the related-work in Table 2.1, Table 2.3, Table 2.4 and Table 2.5.

Based on the related work and related key issues in the field of predictive maintenance and Industry 4.0, the following key requirements can be derived:

- The aspect of flexibility, interoperability and modularity is highly important for achieving a concrete architecture platform for complex Industry 4.0 predictive maintenance.
- Sensor or timeseries data i.e., operation/condition of factory machine equipment tools within an advanced factory manufacturing requires state-of-art techniques such as deep learning for predictive maintenance model.
- The predictive maintenance model driven by deep learning can facilitate data-driven predictive maintenance scheduling, considering different constraints such as multiple machines/components, maintenance resource, cost, and availability.

The different requirements derived from the key issues discussed and identified in Section 2.5 as well as the FIRST industrial cases discussed in chapter 3) lead to forming the requirements for our proposed predictive maintenance for Industry 4.0.

Chapter 3

Industrial Case for Industry 4.0 Predictive Maintenance

In the context of complex manufacturing environment, the performance and condition of the factory machine equipment tools are important to the whole manufacturing process (Sang, Xu, de Vrieze and Bai, 2020*a*). Any unplanned failure or inefficient process of a machine/component of manufacturing factory can have a negative impact for an entire production line, resulting unplanned downtime and associated costs (Sang et al., 2021*a*; Sang, Xu, de Vrieze and Bai, 2020*a*). Traditional maintenance approaches such as manual maintenance is inefficient and cumbersome in collecting equipment data due to the general concern of discrete support, and limited data available from competitive equipment manufacturers. Industry 4.0 enabled technologies such as IoT, RFID/sensor technology enable 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 (Sang, Xu, de Vrieze and Bai, 2020*a*).

The increasing collection of voluminous data and its usage from factory machine equipment tools can offer new opportunities to operations and maintenance process to be proactive with ongoing machine equipment maintenance and upkeep (Sang, Xu, de Vrieze and Bai, 2020*a*). This enables to the optimization of the operation and condition of the machine equipment tools as well as predict future potential issues in a system or equipment, and therefore utilize maintenance in a predictive manner. 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. Subsequently, an optimal maintenance decision can be scheduled for appropriate actions.

In this study, we look at two different industrial application cases in Section 3.1 and Section 3.2 for verifying our proposed solutions i.e., *PMMI 4.0* architecture in Chapter 5, Predictive Model for Maintenance, *MPMMHDLA* in Chapter 6, and Predictive Maintenance Scheduling, *PMS4MMC* in Chapter 7. The application cases are from the industrial cases of the FIRST (vF Interoperation suppoRting buSiness innovation) EU 2020 Project. The two cases i.e. Flexible Manufacturing and Virtual Factory, with some of the corresponding key issues are presented in Section 3.1 and Section 3.2 respectively. And a summary of the key issues related to predictive maintenance in the described cases and potential requirements for Industry 4.0 predictive maintenance is provided in Section 3.3. Lastly, a chapter summary is provided in Section 3.4.

3.1 Flexible Manufacturing Case

In the context of flexible manufacturing, the factory operation is facilitated by several different systems. These systems may include different machine equipment tools such as CPS, robot, processing systems, supply chain management systems, auxiliary systems, and other information systems (Sang, Xu, de Vrieze and Bai, 2020*a*). For FIRST flexible manufacturing case, it operates with four sets of machines, three robots, CNCs, several AGV trolleys, and carrier plates with a warehouse as illustrated in Figure 3.1 and Figure 3.2 (Sang, Xu, de Vrieze and Bai, 2020*a*).

Several machine tools including a coordinate measuring machine, cleaning machine, drying machine are used for different operations e.g. measurement, cleaning and drying the workpiece. The operation of these different machine equipment tools produces various data which can be used for different analytics purpose (Sang, Xu, de Vrieze and Bai, 2020*a*).

The factory operation involves different systems, processes and data from collaborative partners i.e. designers, suppliers, machine manufacturers, etc. in the manufacturing network. In this context, different collaborative business processes exist for different business needs, and hence data are being processed across different domains (Sang, Xu, de Vrieze and Bai, 2020*a*).

In the factory operation setting, the workpiece with high re-positioning accuracy is supported by a universal tray. It enables the ease processing of the workpiece, particularly to be quickly positioned and clamped in various equipment. RFID chip is employed on the tray for identifying each each workpiece. When the workpieces are loaded on a carrier board,

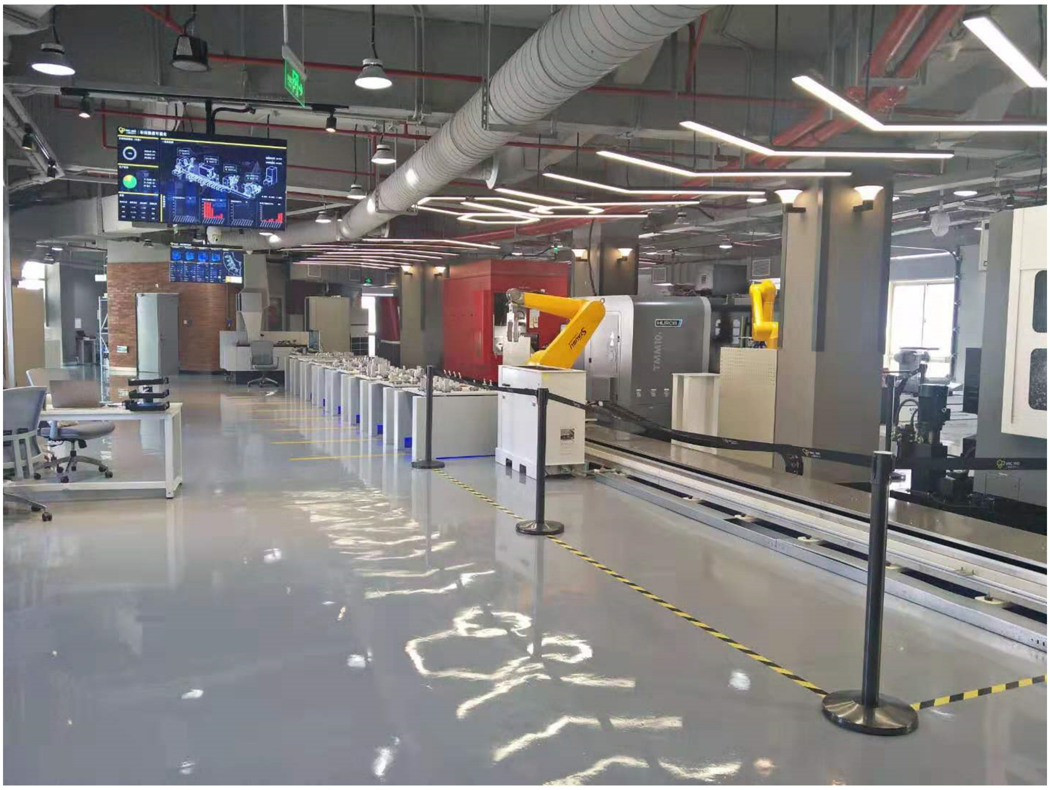


Fig. 3.1 FIRST Flexible Manufacturing (Sang, Xu, de Vrieze and Bai, 2020*b*)

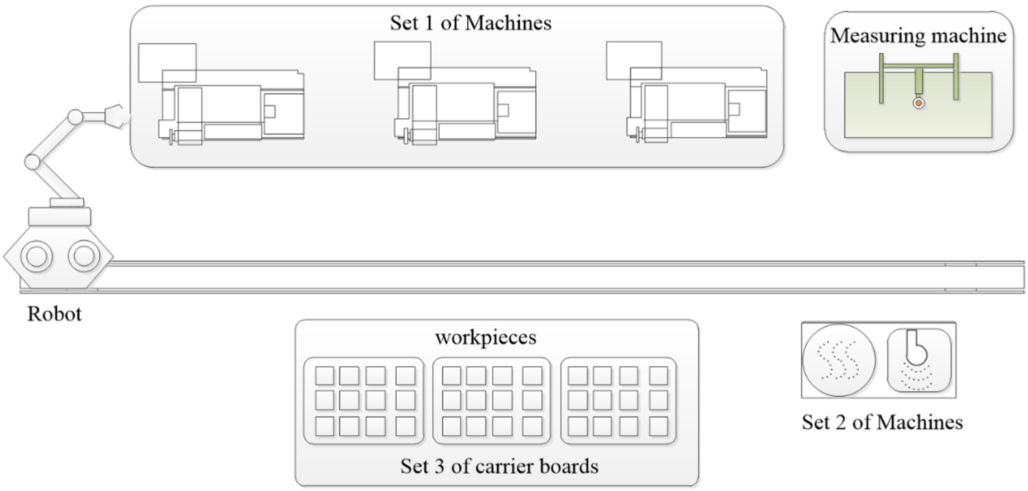


Fig. 3.2 A concrete layout of FIRST Flexible Manufacturing (Sang, Xu, de Vrieze and Bai, 2020*a*)

an AGV is used for transferring the workpieces into the rough machining area (Sang, Xu, de Vrieze and Bai, 2020*a*).

Based on requirements, each workpiece is processed. When the processing of each workpiece is fulfilled, the workpiece is then transferred to further processing. This process concerns with the roughing machining by roughing equipment and the process is assisted by the robot. When the roughing processing is completed, using the robot the workpiece is moved to the cleaning and drying processing. When cleaning and drying processing is finished, the workpiece is placed into the fining section by the robot and is processed for fine machining. The fine machining processing is performed the same way as the roughing machining. The roughing finishing workpiece is placed into the machine using the robot. After processing, it is again placed for cleaning and drying.

At the final stage of the manufacturing process, the quality control process is performed. In this context, the finished workpiece is placed into the quality control section for quality testing. This process is assisted by three-coordinate measuring machine and the robot. If the process is required for different processes such as testing, further processes are carried out. Based on the result, the workpiece is placed into a warehouse or to be packed using AGV. The workpiece may need to be processed again if the quality control is not satisfied with the result.

The flexible manufacturing also works with different collaborative business partners for different business needs. In this context, collaborative business partners such as suppliers, machine manufacturers, insurers, customers involve in the manufacturing network. The business processes are facilitated by collaborative data including product design data, machine base data from manufacturers, machine diagnosis for insurers. The business data are accessed and exchanged across the interactions between each business partners in the manufacturing chain.

3.1.1 Some of the key Issues related to Predictive Maintenance for Flexible Manufacturing Case

Some of the key issues related to predictive maintenance for the Flexible Manufacturing is described as follows.

Manufacturing maintenance downtime and cost: the physical manufacturing machine equipment and systems of flexible manufacturing factory are expensive, and the condition and health of those machines can have a huge impact on the whole manufacturing process. Failures of the machine tools easily can lead to disruptions such as delay, dispute, in the subsequent value-added processes of the organization, partners and its customers, due to the collaborative and interlinked nature of production systems. Essentially, any unplanned failure or inefficient process of manufacturing equipment results in unplanned downtimes and costs for an entire production line.

Complex factory operation involving multiple machines, robots, CNC, etc.: the flexible manufacturing operates with smart systems such as robots, CNC, different information systems and processes as illustrated in Figure 3.1 and Figure 3.2. These different machine equipment tools are required for monitoring and maintaining, to operate factory production operation. This requires an effective management of the factory machine tools, particularly in dealing with maintenance. Current approach relies on conventional reactive and preventive maintenance methods which are expensive, and are not efficient in dealing with the requirements i.e., multiple machines/components, etc., of the manufacturing operation due to complexity as well as cost (Sang, Xu, de Vrieze and Bai, 2020*a*). A new approach is highly desired to facilitate a flexible maintenance platform solution which will facilitate an effective optimization of maintenance process.

Integration (or interoperability) of complex systems/processes/information systems/data sources: predictive maintenance requires the integration of different systems including factory machine equipment tools, processes, information systems, etc., for producing maintenance analytics. Different levels of integration i.e., software, process, machine, etc. exist in the case. For example, different CNC or robot machines require different interfaces for the integration and operating in the production line. Combining the different interfaces by several different machines with related processes without significant effort is important for the whole factory process and for predictive maintenance which requires collecting data i.e., operation, condition, etc., and processing relevant models i.e., predictive failure model, etc., which then can be used for predictive maintenance decision making.

Information Silo: currently, most of the data generated by the factory machines in the flexible manufacturing case are simply stored in the different databases or the log files in different machines. These data ultimately have not been explored or integrated for analytics. A coherent predictive maintenance platform will allow the abilities to easily integrate data from different machines, devices, and systems as well as to easily deploy IoT sensors for monitoring. This requires the predictive maintenance platform facilitating maintenance services are being embedded and optimized with operation and production processes which could achieve optimization for maintenances.

Lack of predictive analytics: currently, the case relies on traditional maintenance activity using manufacturing execution system, different information systems cannot be easily accessible to maintenance engineer when maintenance planning is performed. Both reactive and preventive maintenance tasks are still the core maintenance process. In this context, traditional maintenance processes such as reactive, preventive dealing with maintenance are ineffective, complex, and costly.

Besides, the flexible manufacturing digitalization along with their technologies such as smart machines, robots, CNCs, etc., generate industrial big data, in the form of 4Vs (Volume, Velocity, Variety and Value) (Sang et al., 2017) that challenges for the manufacturing organization, and traditional data processing techniques and tools focusing on structured data before, are not efficient in dealing with such big data generated by the manufacturing processes and machine equipment tools, to produce meaningful information (Sang et al., 2016*c*, 2017; Sang, Xu, de Vrieze and Bai, 2020*a*).

3.2 Virtual Factory Case

Collaborative networks 4.0 is driven by the amalgamation of different processes, partners, third parties, advanced analytics and machines spanning across different enterprises and organizations for collaborative value creations. Industry 4.0 drives the focus of modern manufacturing system design (Koren et al., 2018). It facilitates collaborative processes across different factories and enterprises for complex manufacturing processes. In this aspect, manufacturing related processes are being managed from conventional processes of one organization to collaborative processes i.e. manufacturing processes, product design processes, maintenance processes, across different factories and enterprises (Thoben et al., 2017). Essentially Industry 4.0 enables better control and operations to adapt in real time and in response to constant demands (Porter and Heppelmann, 2014).

The concept of virtual factories derives from the expansion of virtual enterprises in the context of manufacturing (Debevec et al., 2014). Virtual factory is one of implementation of collaborative networks 4.0 in the context of Industry 4.0, and it allows the flexible integration of manufacturing resources in multiple organizations to model, simulate, and test factory layouts and processes in a virtual environment with the support of emerging technologies such as cloud, IoT, etc. This enables the simulation of a desired factory before committing to investment and creating the actual factory in shorter time with demand-driven product lines (Debevec et al., 2014).

Figure 3.3 provides a virtual shoe making factory of the FIRST project. There are numbers of designers, logistics companies, shops and factories involved. Throughout the shoe making process, multiple partners with various business processes are essentially integrated, data is exchanged, collected, and used for optimizing processes e.g. enhancing customer experience and decision-making e.g. optimized supplier process or production process by nearest location of the customer and eco-friendly delivery, etc (Sang et al., 2021*b*).

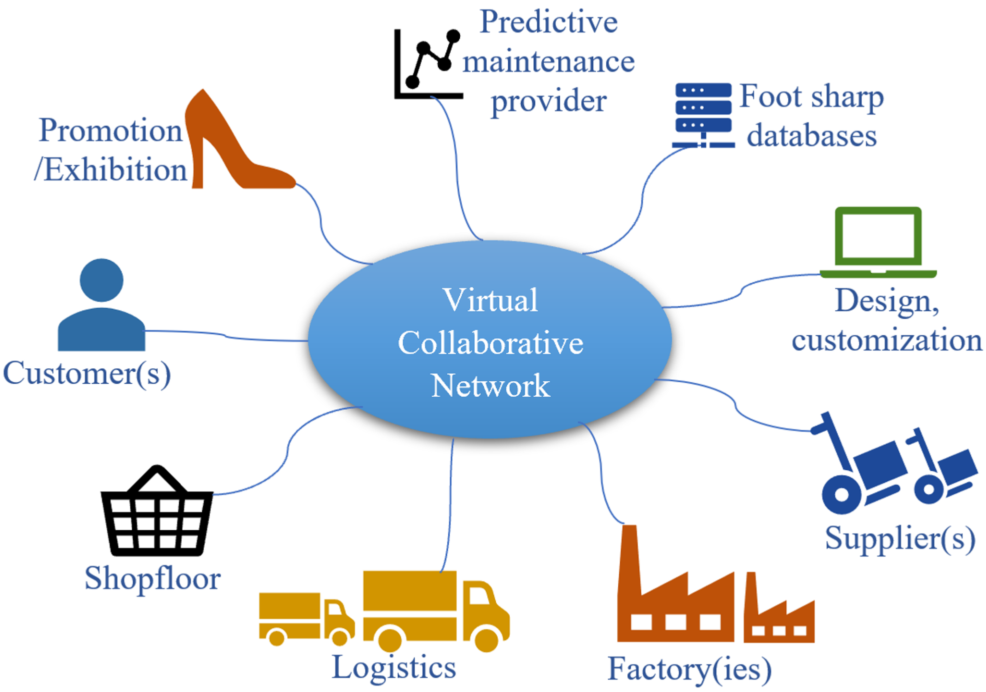


Fig. 3.3 FIRST Virtual Factory Manufacturing (Sang et al., 2021*b*)

In this shoe marking collaborative network, a predictive maintenance service provider is included for supporting machines monitoring and providing maintenance service scheduling for the factories in the collaborative network (Sang et al., 2021*b*).

3.2.1 Some of the key Issues related to Predictive Maintenance for the Virtual Factory Case

Some of the key issues related to predictive maintenance for the virtual factory case is described as follows.

Complex manufacturing collaboration across factory network: advanced manufacturing networks such as the virtual factory case, e.g. virtual factories are not restricted by the physical co-location or long-term collaborations (Porter and Heppelmann, 2014). The variability of different solutions/virtual factory models and how to adapt the potential solutions/virtual factory models, as well as to upkeep and maintenance of various models and tools are challenging for a collaborative manufacturing network environment (Sang et al., 2021*b*). And modern collaborative manufacturing network is complex, and involves modern plant-run machines deployed smart sensors, and robots running on the shop floor as well as a network of collaborations including collaborative business processes e.g. different systems, multiple collaborative partners such as suppliers, manufacturers, designers, customer, etc. (Sang et al., 2021*a*,*b*). Thus, they face different challenges due to the complexity and dynamic nature of the industry collaboration environment. To overcome some of the challenges, advanced capabilities such as predictive maintenance analytics are critically important (Sang et al., 2021*a*,*b*).

Impact of maintenance downtime and cost across the virtual factory network: in the context of virtual factories network, optimization of factory machine equipment tool is critical as it can have a huge impact i.e. downtime, defective product, cost, etc., on the collaborative network processes and partners. Predictive maintenance supports effective collaborative factory operation as it offers the opportunity to act before any event occurs and hence the impact i.e. downtime, cost, etc. can be avoided or minimized (Sang, Xu, de Vrieze and Bai, 2020*a*). Industry 4.0 enables better control and operations to adapt in real time and in response to constant demands. And predictive maintenance is essential to assisting in creating effective maintenance schedule plan for decision making (Sang, Xu, de Vrieze and Bai, 2020*a*). It requires advanced data processing and tools for acquisitioning and processing diverse data from both internal and external sources; data generated by different machine equipment tools, systems and processes, data from networked partner organizations at production and inventory levels, changing consumer demands, and advanced machine learning and optimization techniques for producing information.

Complex system involving multiple machines, robots, CNC, etc., within the virtual factory network: virtual factory predictive maintenance requires the consideration of multiple machine components i.e. different systems/components e.g. IoT devices, CNC machines, tools, etc. operating in Industry 4.0 virtual factories. Traditional monolithic manufacturing organization may operate with its own machine equipment tools, however virtual factories operate across different manufacturing organizations (Sang et al., 2021*b*).

Besides, current maintenance approaches mostly relied on traditional monolithic manufacturing context, the physical structure of the machine component, expert knowledge for both reactive and preventive maintenances, and most importantly they failed to address the consideration of data-driven approach with multiple machine components in the context of multiple organizations/manufacturing factories in collaborative Industry 4.0 setting.

Integration (or interoperability) of complex systems/processes/information: like the flexible manufacturing case, a manufacturing organization within a virtual factory network, operate with different systems, processes, information systems, etc. Predictive maintenance requires the integration of these different systems including factory machine equipment tools, processes, information systems, etc., for producing maintenance analytics. Different levels of integration i.e., software, process, machine, data exchange i.e., collaborative business process, etc. exist in the case. The integration of the different interfaces by several different machines with related processes without significant effort is important for the whole factory process and for predictive maintenance which requires collecting data i.e., operation, condition, etc., and processing relevant models i.e., predictive failure model, etc., which then can be used for predictive maintenance decision making.

Lack of predictive analytics: like the flexible manufacturing case, current virtual factory lies on traditional maintenance activity using MES, different information systems which cannot be easily accessible to maintenance engineer when maintenance activity or planning is performed. Besides, both reactive and preventive maintenance tasks are still the core maintenance process which is costly. Virtual factory, as one of the Industry 4.0 focusing manufacturing digitalization along with their technologies such as smart systems, CPS, IoT, and AI, etc., results in industrial big data, in the form of 4Vs (Volume, Velocity, Variety and Value) (Sang et al., 2017) that challenges for complex manufacturing organizations, and the traditional data processing techniques and tools focusing on structured data before, are not efficient in dealing with such big data generated by the collaborative manufacturing processes and machine equipment tools, to produce meaningful information (Sang et al., 2016*c*, 2017; Sang, Xu, de Vrieze and Bai, 2020*a*).

Furthermore, in a virtual factory network, each firm has its specialized expertise and offers its service to the network. From a predictive maintenance service provider aspect, different machines need to be monitored in multiple organizations within a collaborative network factor. When scheduling a predictive maintenance plan, the predictive maintenance services can be planned as efficiently as possible, for example, the organizations geographical closed may schedule closer to save time, the similar machines in different organizations which similar conditions may change components at the same period to save costs, etc. (Sang et al., 2021*b*).

3.3 Summary of the key Issues in the Industrial Cases and Requirements for Industry 4.0 Predictive Maintenance

Both cases in Section 3.1 and Section 3.2 are driven by advanced collaborative manufacturing. This means that the manufacturing process is facilitated by the integration of agreed business process by different partners to produce a common business goal (Niehaves and Plattfaut, 2011), enabling the collaboration of different manufacturers, factories or business partners. Traditional manufacturing cannot efficiently deal with the challenges such as dynamic market demands, competitions and short product lifecycle (Koren et al., 2018). Moreover, traditional monolithic manufacturing usually involves physical machines, buildings, etc., and setting the manufacturing process is generally slow and expensive (Upton and McAfee, 1996). To overcome the challenges, modern collaborative industries are shifting towards the concept of Collaborative Networks 4.0 (Debevec et al., 2014; Koren et al., 2018; Xu et al., 2019).

Virtual factories as one implementation of Industry 4.0 and a foundational concept to future manufacturing, allow the flexible integration of manufacturing resources from different multiple organizations using emerging technologies such as cloud, sensors, IoT, etc. (Debevec et al., 2014; Sang, Xu, de Vrieze and Bai, 2020*a*; Xu et al., 2020). The concept of collaborative manufacturing network or virtual factory fundamentally changes the way that the traditional factory operates. The traditional monolithic manufacturing heavily relies on its own capabilities e.g. internal functions, physical machines, buildings, etc., whereas the collaborative manufacturing network allows the integration of diverse capabilities from a network of specialized domains and experts across industries collaboratively (Debevec et al., 2014; Xu et al., 2020). This enables the collaborative network better dealing with constant demands of the markets and productivity, since each partner firm focuses on what it does best within the network (Upton and McAfee, 1996), which enables them to operate flexibly and inexpensively regardless of their physical locations.

Data is essential to operating Industry 4.0 manufacturing (Sang, Xu, de Vrieze and Bai, 2020*a*). Data generated by the various processes, systems/machine component tools across factories operation and production offer opportunities such as data-driven analytics e.g. predictive maintenance (Sang et al., 2016*c*, 2017; Sang, Xu, de Vrieze and Bai, 2020*a*; Thoben et al., 2017) to the collaborative network. Effective maintenance is essential to the factory operation as well as the collaborative manufacturing network, to reduce downtime, cost and avoid faulty products which can impact on the collaborative chain i.e. integrated processes and value (Sang, Xu, de Vrieze and Bai, 2020*b*; Sang, Xu, de Vrieze, Bai and Pan, 2020). Flexible collaboration with other businesses is an important aspect of a collaborative manufacturing network (Xu et al., 2020). In this sense, a collaborative network partner, as a service provider can offer data-driven predictive maintenance across the collaborative network i.e. manufacturers, factories, etc.

As the manufacturing process such as the described cases, becomes more and more complex, it is hard to effectively identify the problems arising in the manufacturing process by the traditional approach. These potential maintenance problems in modern manufacturing can only be detected by the application of advanced capabilities such as big data processing, tools, and analytics. Currently, most of the data generated by the factory production machines in the Flexible Manufacturing case are simply stored in the different databases or the log files in different machines. These data ultimately have not been explored for analytics. A coherent predictive maintenance platform would facilitate the abilities to easily integrate data from different machines, devices, and systems as well as to easily deploy IoT sensors for monitoring. In this way, the maintenance services are developed, embedded, and optimized with operation and production processes which could achieve optimization for maintenances.

To achieve an effective modern manufacturing in the context of industry 4.0, a new approach of maintenance services should be in place to provide a flexible platform. This platform enables dynamic and advanced capabilities of predictive maintenance. The services provided in the platform align with industry 4.0 standards, architecture, and other related technologies (Sang et al., 2021*a*).

3.3.1 Some key Requirements of the Industrial Cases for Industry 4.0 Predictive Maintenance

Some requirements derived from key issues related to predictive maintenance for the cases are described as follows.

- Multiple machine components operate in factory operation, any failure can have significant impact – downtime and cost to the collaborative domain.
- Different data sources, information systems, ERP, MES, etc., make it difficult to have effective analytics.
- Reliance on both manual and MES for maintenance activity and plan.
- A flexible architecture platform which facilitates to easily integrate different systems, processes or components which are required for predictive maintenance.
- Advanced capabilities in dealing with big data and maintenance analytics, particularly data-driven approach utilizing state of the art techniques such as deep learning for predictive model and predictive maintenance scheduling with the consideration of the complex systems i.e., multiple machine equipment tools involved in the factory production line.
- Modular capability in dealing with dynamic business requirements and the ability to easily add or change new or existing systems/components/processes.
- Potential opportunity for predictive maintenance as service, particularly virtual factory.

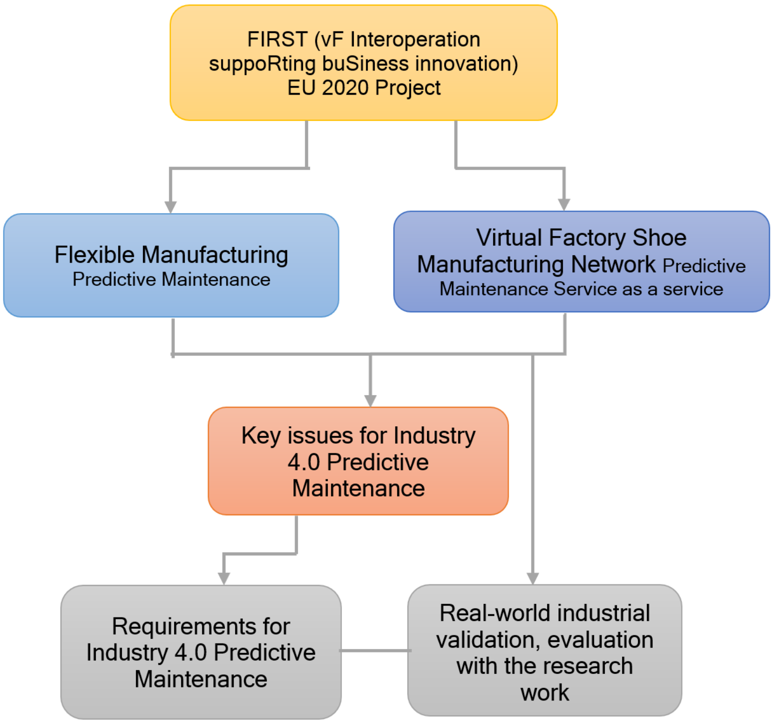


Fig. 3.4 Relation between research challenges, requirements, verification and EU H2020 FIRST project

3.4 Chapter Summary

This chapter presents the Industrial Case for Industry 4.0 predictive maintenance, describing Flexible Manufacturing and Virtual Factory cases of the FIRST project. Some of the key issues of both cases that are subject to Industry 4.0 predictive maintenance are presented. These include key requirements such as flexible architecture platform, interoperability, modularity, and advanced capabilities such as big data analytics e.g., maintenance analytics, services, etc. The industrial cases were applied to the proposed research work in the corresponding Chapters 5 – 7 for validation and evaluation analysis as illustrated in Figure 3.4.

Chapter 4

Methodology

This chapter presents the methodology used to answer the research questions stated in chapter 1. This chapter describes the procedural steps, research approach used to accomplish the research. The chapter is structured as follows: Section 4.1 presents the conceptual framework which is subject to the research work. Section 4.2 presents the research philosophy which is embraced with the research methodology. Section 4.3 describes different research methods that are applied to the research approach in the study. In Section 4.4, we present how design science was applied to achieve the artifacts of the research by following the recommended steps adopted from Section 4.3. The chapter concludes with summary in section 4.5.

4.1 Conceptual Framework of Research Methodology

The conceptual framework of the research methodology presented in Figure 4.1 provides a conceptual foundation upon which the concepts in the study are derived. The Industry 4.0 paradigm is the focus of modern manufacturing system design. Industry 4.0 focusing manufacturing systems are facilitated by the integration of cutting-edge technologies such as Internet of Things, Cyber-Physical Systems, Big Data Analytics, and high computation which requires a flexible architecture platform supporting the effective optimization of manufacturing-related processes, e.g. predictive maintenance. Existing maintenance studies generally focus on conventional approaches such as reactive or preventive, which are based on model-based or experience-based model without considering the maintenance decisions or maintenance optimizations. To achieve an effective maintenance in the context of industry 4.0, a new approach of maintenance services should be in place to provide a flexible platform. This platform enables dynamic and advanced capabilities of predictive maintenance. The services provided in the platform align with industry 4.0 standards, architecture, and other

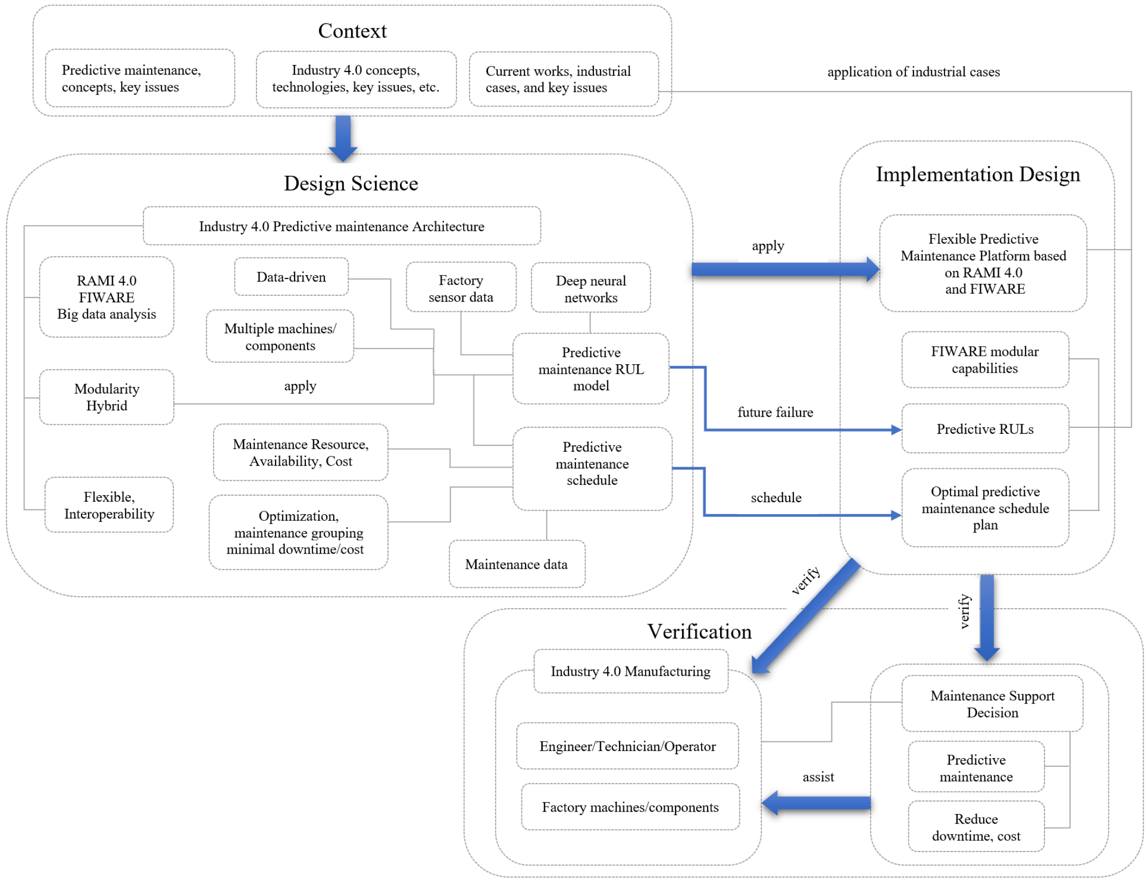


Fig. 4.1 Conceptual framework of research methodology

related technologies. Analysis of the key issues, concepts, and requirements from Industry 4.0 and maintenance led to formulation of the research question and related scope, objectives and aims of the research.

A brief description of the major concepts is provided (Sang et al., 2021*a*; Sang, Xu, de Vrieze and Bai, 2020*a*):

- Industry 4.0 supports the flexibility required for the manufacturing network by the application of advanced technologies such as the internet of things (IoT), Cyber Physical Systems (CPS), big data analytics, cloud computing, etc. which are utilized for operating the intelligent machines and processes in the factory network context.

- Predictive maintenance facilitates advance detection of pending failures and enables timely pre-failure interventions, using different prediction tools based on various data i.e. historical operation, condition, etc., and different machine/deep learning approaches.

- Flexibility the ability to easily integrate different systems, machines, components, tools, processes for business requirements.
- Modularity the ability to add or adapt new business requirements into existing systems/processes without significant effort.
- RAMI 4.0 provides a simplified architecture of Industry 4.0 complex systems, processes, etc.
- FIWARE an implementation platform of RAMI 4.0 for Industry 4.0 which supports open and modular framework.
- Predictive maintenance RUL model data-driven predictive maintenance model for remaining useful life estimation.
- Predictive Maintenance Scheduling data-driven predictive maintenance scheduling driven by RUL.
- Optimization considers for the aspect of Industry 4.0, particularly multiple machines/components predictive maintenance scheduling with grouping maintenance, reducing cost.

4.2 Research Philosophy

The discipline of this study lies in science. The philosophy of science is recognized as the study of the elements of scientific inquiry from a philosophical perspective (Kitcher, 2019). A philosophical paradigm can involve a set of shared assumptions and ways of thinking about the nature of our world i.e., ontology and the ways knowledge about it can be acquired i.e., epistemology (Richardson, 2006).

Three philosophical paradigms of research are discussed by Richardson (2006), namely positivism, interpretivism, and critical research. For the study of the natural world, positivism is suitable, while interpretivism and critical research are more appropriate when studying the social world as they assume that there are multiple subjective realities as social reality is created and re-created by people.

Positivism can be further divided into positivist and post-positivist approaches. In the positivist approach, it is assumed that the world is regular and ordered and can be investigated objectively. Research is based on the empirical hypothesis testing, leading to their confirmation or refutation. Finally, it aims to discover universal laws that can be shown to be true regardless of circumstances.

Fig. 4.2 A Representation of Qualitative Method (Queirós et al., 2017)

The post-positivistic approach argues that research evidence is always imperfect and fallible (Robson and McCartan, 2016). Therefore, reality can only be known imperfectly and probabilistically because of researcher limitations. In contrast to the positivist approach, it accepts that what is observed can be influenced by theories, hypotheses, background knowledge and the values of the researcher (Reichardt and Rallis, 1994).

In this work, due to the nature of research context i.e., Industry 4.0 manufacturing and predictive maintenance, the positivist philosophical paradigm is embraced with the applied methodology in Section 4.4. In this way, real-world industrial cases can be objectively investigated, observed, and that concrete contributions can be made.

4.3 Research Approach

4.3.1 Qualitative and Quantitative Method

Generally, research work can be carried out either qualitative or quantitative method in various research fields. The qualitative method focuses on quality and non-numerical data, enabling to get an understanding of the research problem in a comprehensive manner. On the other hand, the quantitative method is based on the different aspect of measurement using different statistical techniques in numerical data (Kothari, 2004).

Qualitative method intends to understand a complex reality and the meaning of actions in a given context as shown in Figure 4.2. Maxwell (2012) implies that qualitative research works with in the field of meanings, motives, beliefs, values and attitudes, which corresponds to a deeper space of relationships, processes and phenomena that cannot be reduced to the

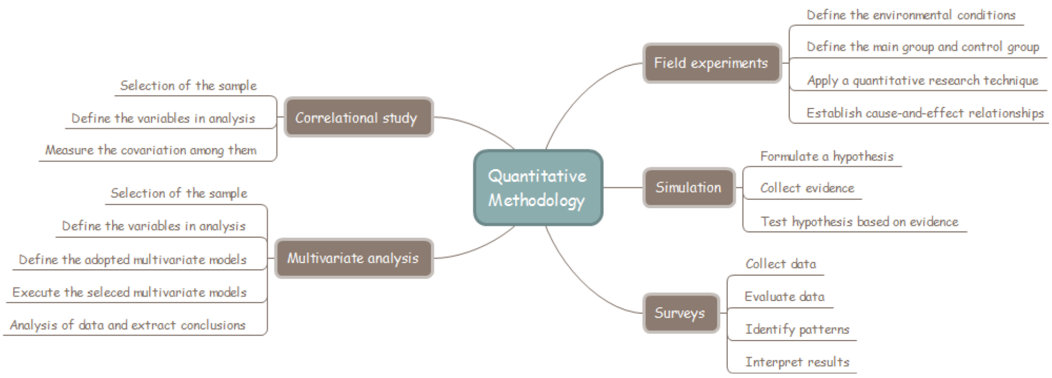


Fig. 4.3 A Representation of Quantitative Method (Queirós et al., 2017)

operationalization of variables. Generally, surveys and correlational studies are the most common methods to perform a quantitative research (Queirós et al., 2017).

A representation of quantitative method is presented in Figure **??**. The quantitative research focuses on objectivity and is especially suitable when there is the possibility of collecting quantifiable measures of variables and inferences from samples of a population. Quantitative research utilizes structured procedures and formal instruments for data collection. The data are collected objectively and systematically. The analysis of numerical data is performed through statistical procedures, often using software such as SPSS, etc. (Queirós et al., 2017).

4.3.2 Design Science

Peffers et al. (2007) presented a design science research methodology for information systems research as shown in Figure 4.4. The purpose of this model is to provide a framework to carry out design science research as well as a template model for its presentation (Peffers et al., 2007). The guidelines for design science research as presented by Hevner et al. (2004) cover the following aspects: design as an artefact, problem relevance, design evaluation, research contribution, research rigor, design as a search process, and communication of research (Hevner et al., 2004).

Design science involves three interrelated cycles of Relevance, Design and Rigour as shown in Figure 4.5 (Hevner et al., 2004). The relevancy cycle intends to enhance the environment, that is the problem space, by providing relevant solutions, in form of artifacts to existing problems. The artifacts are then evaluated at the environment. This leads to rigorous testing of the artifact for release. This can be done iteratively before the artifact goes to the relevance and rigour cycles. The rigour cycle refers to the application of knowledge from well-known scientific theories and engineering methods. Knowledge may come from experiences

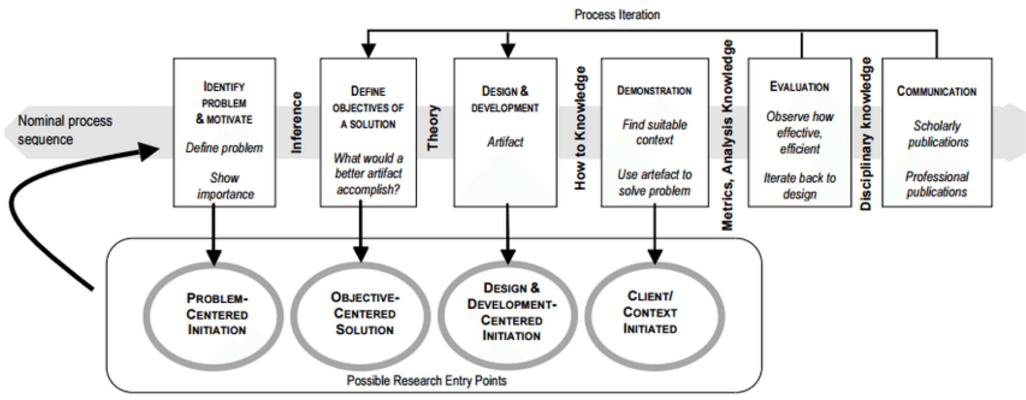


Fig. 4.4 Process model of design science research methodology (Peffers et al., 2007)

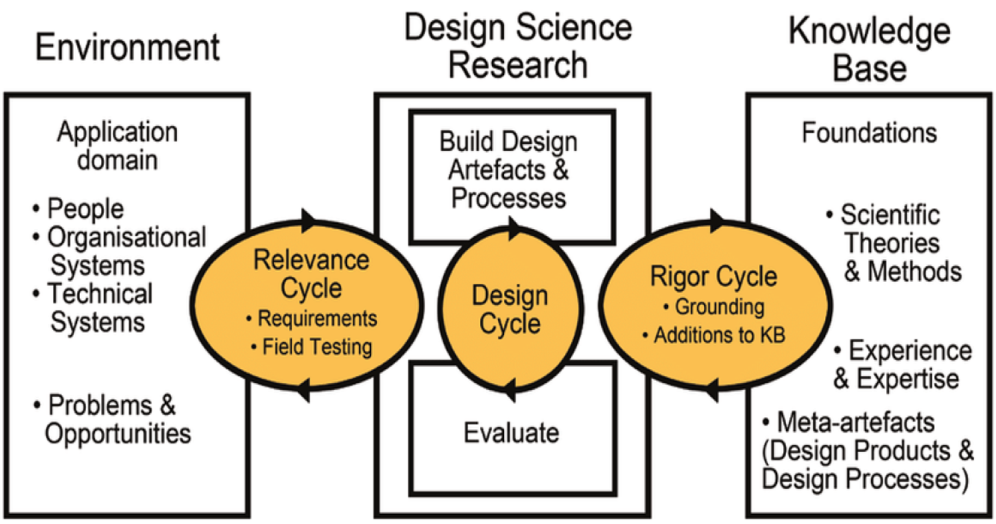


Fig. 4.5 Design science research cycles (Hevner et al., 2004)

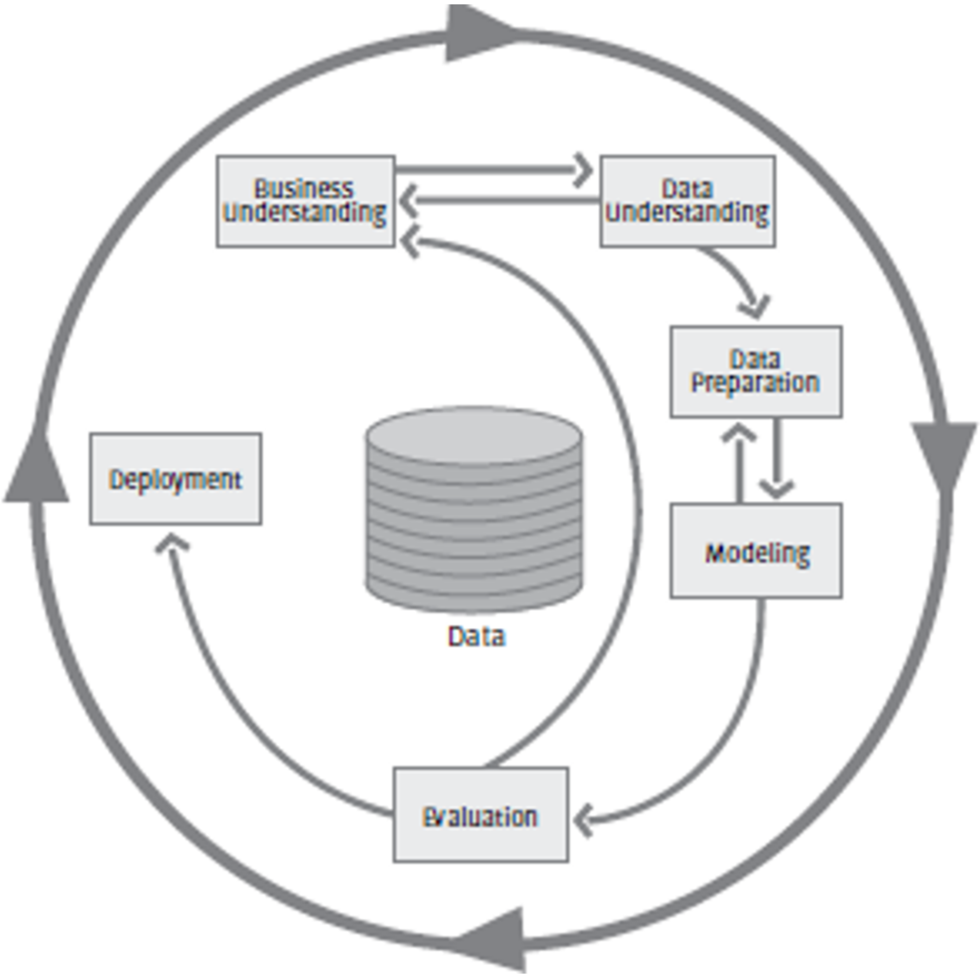


Fig. 4.6 CRISP-DM Cycle (Chapman et al., 2000)

and expertise that define state of the art or existing artifact and processes. The relation to the knowledge base enables a new or innovative artifact is presented as a contribution. As an iterative process, design cycle encourages the design and evaluation of the artifact. In this way, feedback from the evaluation, is utilized to fine tune the artifact to its final release.

4.3.3 CRISP-DM

CRISP-DM, Cross Industry Standard Process for Data Mining is a data analysis process model that defines commonly used methods that industrial experts use to tackle business problems (Chapman et al., 2000). CRISP-DM consists of six different stages as shown in Figure 4.6 including business understanding, data understanding, data preparation, modelling, evaluation, and development, which are processed iteratively.

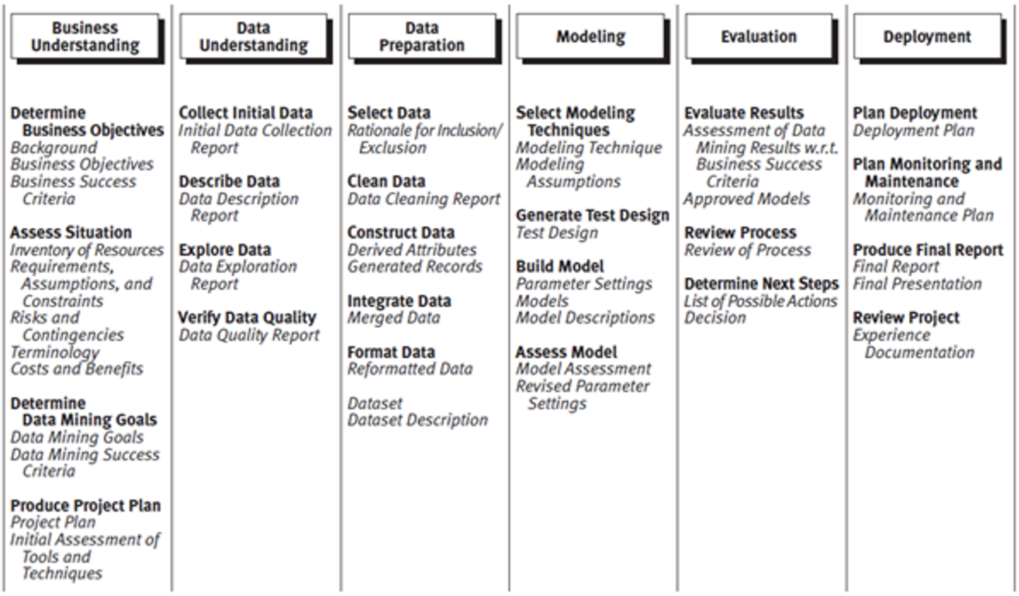


Fig. 4.7 CRISP-DM Process (Chapman et al., 2000)

The method is described in more detail in Figure 4.7, outlining the different tasks conducted at each stage.

Data and model selection, rather than the business objectives, are the focus of CRISP-DM. In this aspect, model selection has a significant influence over the process and that can lead into different business objectives (Sang et al., 2016*b*,*c*). Moreover, the status of available data i.e., correct, valid format, etc., may not meet the requirement of the business objectives. Thus, the consideration of the different aspect such as the available data, business objectives and techniques should be initially recognized. Then, it proceeds to the selection of models, only at the modelling stage.

Furthermore, data processing or preparation may require for each iterative model to work effectively (Sang et al., 2016*b*,*c*). This can slowdown the whole process as a model is developed and data processing is reviewed only after the data preparation is carried out. However, this can be resolved by revising the data preparation as needed.

4.4 Research Methodology

The research work conducted in this thesis is large-scale information system which is in the field of predictive maintenance under information systems research. Information systems and computing research should be relevant and rigorous (Hevner et al., 2004). Design science relies upon the application of rigorous methods in both the construction and evaluation of

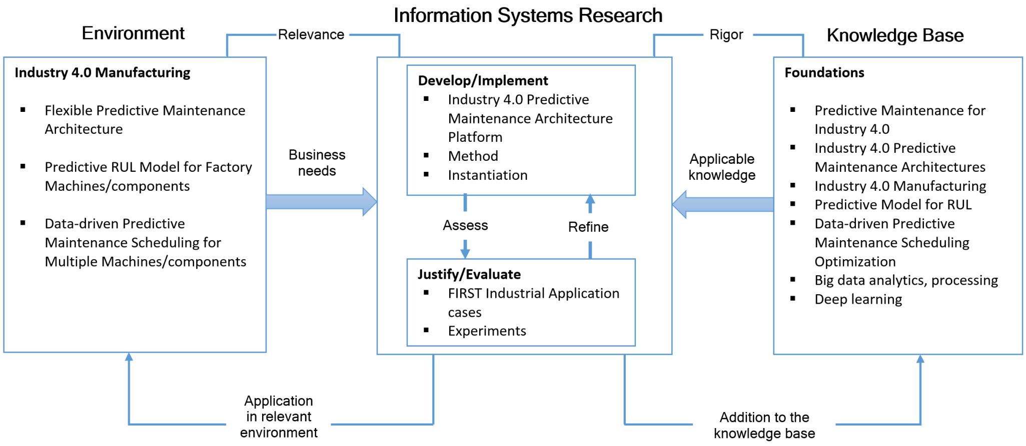


Fig. 4.8 Research method mapped with information systems research

the design artefact, compared with other methods such as qualitative method, quantitative method which focuses on quality and non-numerical data in Section 4.3.1. Based on the field of predictive maintenance and Hevner et al. (2004), the research work conducted in this thesis belongs to design science in information systems. Design science is the most suitable method and hence is adopted for this study.

The application of Information Systems Research and Design Science for the research study is explained in Section 4.4.1 and Section 4.4.2 respectively.

4.4.1 Application of Information Systems Research

In this study, the research methodology is based on the guidelines presented by Hevner et al. (2004) and the methodology described by Peffers et al. (2007). The research method mapped with the information research methodology is presented in Figure 4.8.

The iterative process of design and development is captured in the information system research framework presented by Hevner et al. (2004). The instantiation of the framework for this research is presented in Figure 4.8. The design and creation i.e. development research strategy focus on developing new IT artefacts (Hevner et al., 2004; Peffers et al., 2007). Researchers following this strategy can contribute to knowledge with a construct, model, method, instantiation, or combination of those. According to Hevner et al. (2004); March and Smith (1995); Peffers et al. (2007); Reichardt and Rallis (1994):

- construct is the concept or vocabulary used in a particular IT-related domain,
- model is a combination of constructs that represent a situation and is used to aid problem understanding and solution development,

- method is guidance on the models to be produced and process stages to be followed to solve the problems using IT,
- instantiation is a working system which demonstrates that constructs, models, methods, ideas, or theories can be implemented in a computer-based system.

In our method in Figure 4.8, the environment describes Industry 4.0 manufacturing with identified problems which drives the requirements for corresponding artifacts for the develop/implement, based on the knowledge and challenges derived from the knowledge base. The experiments is done via the FIRST industrial cases for evaluation at justify/evaluate. The detail process of the research methodology in Figure 4.8 is explained in the Research Process at the next Section.

The main artefacts and contributions of the research are:

- Predictive Maintenance Model for Industry 4.0 (PMMI 4.0), a flexible architecture platform for Industry 4.0 predictive maintenance
- Modular Predictive Maintenance Model using Hybrid Deep Learning Approach (MP-MMHDLA), predictive maintenance RUL model for Factory machines/components utilizing hybrid deep neural network and factory sensor operation and condition data
- Predictive Maintenance Schedule for Industry 4.0 Multiple Machines and Components (PMS4MMC) which is driven by the proposed Predictive RUL model and maintenance data for optimization of predictive maintenance scheduling.

4.4.2 Application of Design Science for the Research Process

The research process in this work is mapped into the Process model of design science research methodology by Peffers et al. (2007), as shown in Figure 4.8. We explain the process as follows.

4.4.2.1 Research Entry Point

The research project is initiated from the H2020 FIRST Project. The FIRST project aims to provide new technology and methodologies to describe manufacturing assets; to compose and integrate existing services into collaborative virtual manufacturing processes; and to deal with evolution of changes. One key objective is applying Industry 4.0 predictive maintenance in industrial research partners' cases including Flexible Manufacturing (i.e. Section 3.1 in Chapter 3) and Virtual Factory (i.e. Section 3.2 in Chapter 3). In this instance, a flexible architecture for Industry 4.0 is required for supporting predictive maintenance, avoiding faults and disturbances, and enhancing the optimization of maintenance process for the machines/components involved in the production line. To be relevant, the project has to be aligned with the business strategy, which meant that it has to:

- Flexible architecture platform
- Modular integration of different components and processes
- Use collected factory sensor operation/condition data to predict events in the status of machines/components
- Assist to support maintenance scheduling that reduce cost and downtime
- Acquire the data from existing factory machines/components within the FIRST industrial cases.

The specified requirements are at a high level of abstraction, and a pre-study is performed to further shape the research.

4.4.2.2 Problem Identification and Motivation

Problem identification and justification are done through a literature study and observation of maintenance work in the FIRST Industrial cases. The problem is motivated by the emerging Industry 4.0 and predictive maintenance problems and challenges despite existence of several approaches. The solution targets users such as maintenance engineer, technician, factory staff, etc., that need support to effectively manage predictive maintenance in complex Industry 4.0 manufacturing environment. Existing architecture and predictive maintenance solutions are still not designed in complying with Industry 4.0 standards i.e., modularity, interoperability as well as do not target multiple machines/components that operate in Industry 4.0 environment. Both the problem and motivation are also covered in Chapter 1 as well as related sections in Chapter 2.

4.4.2.3 Objective of the Solution

The objective of the solution is derived from the research questions. The research questions guide the study by providing a direction, research goals and scope towards the solution. From the industrial business perspective, the developed artefact is required to have a positive impact (quantitative objective) on one or more key indicators, for example, cost, overall machine efficiency, effective maintenance schedule plan, flexible integration of different systems/machines/processes and ultimately, the predictive maintenance can be provided as a service in the context of Industry 4.0.

4.4.2.4 Design and Development

To achieve the design, an artifact in form of a flexible Industry 4.0 Predictive Maintenance approach is to be developed that includes among other components;

- *Predictive Maintenance Model for Industry 4.0 (PMMI 4.0)*, a flexible architecture platform for Industry 4.0 predictive maintenance
- *Modular Predictive Maintenance Model using Hybrid Deep Learning Approach (MPMMHDLA)*, predictive maintenance RUL model for factory machines/components utilizing hybrid deep neural network derived from factory sensor operation and condition data supporting modularity
- *Predictive Maintenance Schedule for Industry 4.0 Multiple Machines and Components (PMS4MMC)* which is driven by the proposed Predictive maintenance RUL model and maintenance data for the optimization of predictive maintenance scheduling

Applying the adapted CRISP-DM approach (i.e. Predictive Model for Maintenance in Chapter 6), business case i.e., predictive failure detection of machines/components of FIRST industrial case is identified and factory sensor operation/condition data collected from the industrial case is to be utilized for developing *Modular Predictive Maintenance Model using Hybrid Deep Learning Approach (MPMMHDLA)* which is discussed in Chapter 6.

Specifically, the predictive model and maintenance scheduling will be performed in an iterative way, beginning with data acquisition through data processing to maintenance schedule planning for decision-making.

4.4.2.5 Demonstration

The developed solution is to be applied to real world industrial setting and related data. Data obtained from the manufacturing is used to build data-driven models as well as to demonstrate predictive maintenance schedule plans. Chapter 5 presents the demonstration of the proposed *Predictive Maintenance Model for Industry 4.0 (PMMI 4.0)* and application case in FIRST industrial project. Chapter 6 presents the proposed *Modular Predictive Maintenance Model using Hybrid Deep Learning Approach (MPMMHDLA)* utilizing factory machine/component operation/condition data, and then the model is used for supporting *Predictive Maintenance Schedule for Industry 4.0 Multiple Machines and Components (PMS4MMC)* using maintenance related data in Chapter 7.

4.4.2.6 Evaluation

Evaluation is to be performed via experiments with the FIRST industrial scenario cases for *PMMI 4.0, MPMMHDLA and PMS4MMC*. *PMMI 4.0* architecture is evaluated as ChapterChapter 5 presents assessing its applicability and effectiveness to verify flexible integration of FIRST flexible manufacturing case. Section 5.4.2 and Section 5.4.3 in Chapter 5 will report the evaluation analysis regarding modularity, interoperability, and advanced capabilities such as related predictive model and maintenance analysis, etc., and subsequent comparison results with existing approaches will be carried out for the validity of our *PMMI 4.0* approach for Industry 4.0 predictive maintenance.

Similarly, real-world industrial data are to be used for developing *Modular Predictive Maintenance Model using Hybrid Deep Learning Approach (MPMMHDLA)* as Chapter 6 will demonstrate the performance of the developed RUL model for machines/components of the FIRST industrial case. The performance results and comparisons with existing methods in Section 6.4.2 will show the effectiveness of our method for real-world Industry 4.0 manufacturing application.

Predictive Maintenance Schedule for Industry 4.0 Multiple Machines and Components (PMS4MMC) which is driven by the proposed Predictive maintenance RUL model and maintenance data for the optimization of predictive maintenance scheduling was assessed using FIRST flexible manufacturing and Virtual Factory cases as Chapter 7 will discuss its applicability and verification. Section 7.3 will report the outcome of the scenario cases derived from the industrial maintenance data where predictive maintenance scheduling can be planned for multiple machines/components considering maintenance related task, cost, resource, and availability. Dynamic approach for flexible inputs to generate an optimal cost or downtime based on predictive maintenance RUL values and maintenance related information can be achieved. The direct cost of maintenance actions based on different approaches is to be compared.

The outcome of the evaluation for our predictive maintenance model for Industry 4.0 *(PMMI 4.0)*, Predictive maintenance RUL model *(Modular Predictive Maintenance Model using Hybrid Deep Learning Approach - MPMMHDLA)* and predictive maintenance scheduling for multiple machines/components *PMS4MMC* will demonstrate the applicability and effectiveness of the solution to solving Industry 4.0 predictive maintenance problem. Besides, it will confirm that the architecture platform is flexible enough to support Industry 4.0 manufacturing as well as the predictive model and PMS4MMC algorithms are expressive enough to meet the requirements for the industrial use cases.

4.4.2.7 Communication

The research has been published in academic journals, academic conference proceedings, and industrial settings; EU H2020 FIRST project, knowledge application to the industry with FIRST flexible manufacturing and Virtual Factory as previously described in Chapter 3.

4.4.2.8 Contribution

The method is developed and demonstrated on real-world industrial cases of the FIRST project that are of high importance. A summary of contributions is presented in Chapter 8.

4.4.2.9 Relevance and Rigor

Information systems and computing research should be relevant and rigorous (Hevner et al., 2004). The objective of the design science research approach is to develop a technology-based solution for important and relevant business problems (Hevner et al., 2004). This study is initiated by the H2020 FIRST Project and industrial partners, moreover, the relevance and importance of the problem is confirmed through a literature study. Relevance is defined as having a direct impact on practitioners. The practitioners in this thesis are other developers of Industry 4.0 predictive maintenance systems. As the research conducted is closely related to the real industrial problem, it could be relevant to decision makers or maintenance engineers/managers to justify putting more effort into predictive maintenance.

Design science research relies upon the application of rigorous methods in both the construction and evaluation of the design artefact (Hevner et al., 2004). The work presented follows a systematic process, applied methods are verified and evaluated, and validity is considered. For example, when the predictive RUL for the machines/components was predicted, the predicted RUL values were matched with the actual data obtained from the operation data of machine/components of the industrial case. Besides, real-world industrial cases for PMMI 4.0 as well as industrial related data such as maintenance, etc., for *PMS4MMC* are used for the evaluation and validation and comprehensive comparison analysis is carried out with existing approaches.

External validity is concerned with the level of generalizability. It depends on how representative the research samples are (Richardson, 2006). The external validity of method evaluation is lower, since data from a limited number of machines or industrial cases are analysed. This means that the results in a different case cannot be evaluated ahead of time. However, our approach focuses on modularity and interoperability for Industry 4.0 complying with its standards, as well as does not make many assumptions, our solution PMMI 4.0 with

MPMMHDLA and *PMS4MMC* can be adapted and applied to different cases, which is also one of our future works e.g., journal paper 3 in pending submission.

4.5 Chapter Summary

This chapter presented the methodology followed to accomplish the goals and objectives of this research. The research process started with the problem of Industry 4.0 predictive maintenance and related concepts i.e., knowledge base as described in Figure 4.8 which provided a technical foundation for the study's Industry 4.0 predictive maintenance discipline and then followed using the model by Peffers et al. (2007).

Design science is adopted based on analysis of other IS research methods as the justification presented. The research steps from the design science were adopted to accomplish the study. As Figure 4.9 shows, these steps, including an approach for predictive model based on CRISP-DM (Chapman et al., 2000) (i.e. detailed approach is described in Chapter 6), are mapped into our approach for designing and developing *PMMI 4.0, MPMMHDLA and PMS4MMC* indicating what research outcomes for each chapter. The corresponding evaluations and results of the chapters (5, 6 and 7) are presented in each chapter.

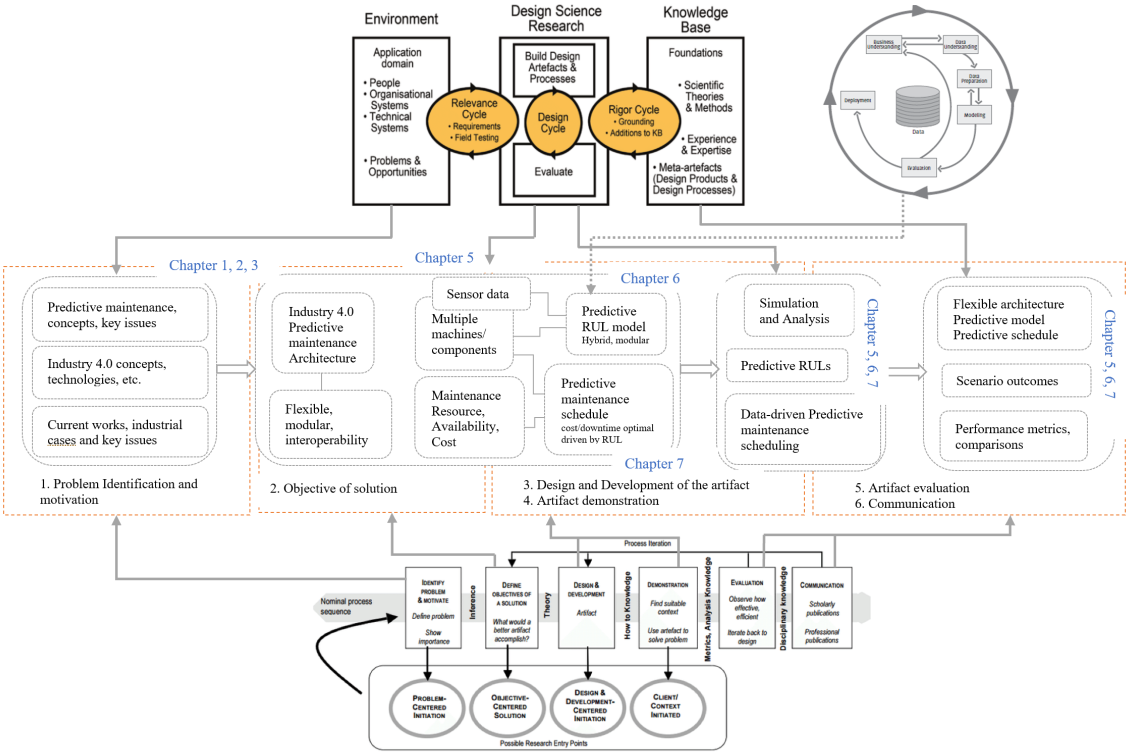


Fig. 4.9 Research process mapped into design science steps (Peffers et al., 2007), research cycles (Hevner et al., 2004) and CRISP-DM (Chapman et al., 2000)

Chapter 5

Predictive Maintenance for Industry 4.0

Modern collaborative manufacturing industries are advancing to embrace the concept of Industry 4.0 in achieving high levels of productivity and flexibility (Zezulka et al., 2016). Modular collaboration is essential to enabling the flexibility (pluggable components i.e., processes, machine, devices) for cross-organization to work seamlessly (Koren et al., 2018; Thoben et al., 2017; Zezulka et al., 2016). 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. This however requires the underlying system flexible enough to support the dynamic nature and needs of complex manufacturing systems. Besides, based on predictive maintenance in Industry 4.0 maturity as discussed in Section 2.2.1, the key issues and related requirements described in Section 2.2.5 and Section 2.5, it is clear that there is an opportunity for Industry 4.0 predictive maintenance capability. This demands a predictive maintenance with a flexible platform that supports predictive maintenance in Industry 4.0 maturity as well as complex collaborative manufacturing.

To support Industry 4.0 manufacturing systems, different architectures and predictive maintenance implementations are proposed (Lee et al., 2015; Lin et al., 2017; Zezulka et al., 2016). In the context of Industry 4.0 architecture, Lee et al. (2015) proposed a 5C architecture for designing smart manufacturing systems. 5C architecture involves five levels of steps for the realization of cyber-physical systems (CPS) with the levels smart connection (I), data-to-information conversion (II), cyber (III), cognition (IV), and configuration (V) which are done in a sequential manner. The approach may not be flexible for the modern industry to deal with dynamic changes and demands, particularly in complex Industry 4.0 setting. Industrial Internet Reference Architecture (IIRA) is a reference model for industrial internet of thing (IoT) systems (Lin et al., 2017). It specifies an Industrial Internet Architecture Framework comprising viewpoints and concerns to aid in the development, documentation, and communication of the IIRA. It focuses on the architecture of IoT system in the organization, however it lacks the consideration for Industry 4.0 context whereas complex collaborative systems/machines/processes operate in a complex network. Thus, it is suitable for enterprise (smart) system, ideally for enterprise architecture of predictive maintenance. On the other hand, Reference Architecture Model for Industry 4.0 (RAMI 4.0) focuses on the overall architecture of Industry 4.0 organizations by simplifying the complex processes and systems (Zezulka et al., 2016). Due to its simplified model and compliance with Industry 4.0 standards, RAMI 4.0 architecture thus is an ideal architecture solution, compared with other approaches such as 5C architecture and IIRA that only focus on IoT or CPS system.

Predictive maintenance implementation platform is as high important as the architecture itself. In the context of predictive maintenance for Industry 4.0, several solutions have been proposed. Bagheri et al. (2015) extend the 5C architecture of Lee et al. (2015) where it focuses on cyber-physical systems architecture for self-aware machines in designing and implementing the framework for interconnect systems in an enterprise environment. Chiu et al. (2017) presented a predictive maintenance architecture focusing on a manufacturing cell, which mostly deals with monitoring the equipment tools within a manufacturing context. A semantic cloud architecture framework for predictive maintenance was proposed by Schmidt et al. (2017). Their approach was based on domain ontology and was derived from challenges such as different domain data existed for predictive maintenance. Thus, these approaches mainly deal with the aspect of data collection and analysis for predictive maintenance architecture solution for a certain system or machine e.g., CPS, within a manufacturing or an organization context, and they fail to address the challenges of flexibility (required for the integration of different systems/machines/processes), a significant aspect of operating Industry 4.0 predictive maintenance in complex collaborative networks.

To achieve an effective Industry 4.0 predictive maintenance solution, an approach of maintenance services should be in place to provide a flexible architecture platform. This platform enables dynamic and transparent collaboration and advanced capabilities of predictive maintenance. The services provided in the platform align with industry 4.0 standards, architecture, and other related technologies. Thus, we propose *Predictive Maintenance Model for Industry (PMMI) 4.0* which is based on a modular architecture platform, supporting key capabilities such as data acquisition, prediction as well as maintenance.

In this section, the concepts, process, and predictive maintenance for Industry 4.0 are discussed and presented in Section 5.1. The proposed predictive maintenance model for Industry 4.0 (PMMI 4.0) is described in Section 5.2. PMMI 4.0 implementation environment for FIRST manufacturing case is presented in Section 5.4. And a summary of the chapter is provided in Section 5.5. This chapter contains the published Paper 1[1], Paper 2[2], Paper 5[3] and Paper 6[4].

5.1 Concepts, Process and Predictive Maintenance for Industry 4.0

5.1.1 Concepts of Industry 4.0 Predictive Maintenance

Industry 4.0 provides new opportunities and concepts for monitoring and optimizing the manufacturing operations (Zezulka et al., 2016) such as predictive maintenance. These concepts offer a general framework to the main requirements of Industry 4.0 and are discussed here with specific references to Industry 4.0 predictive maintenance.

Interoperability: the ability of different manufacturing CPS, machines, robots, and workers to connect and communicate via a network such as IoT and IoS. Different levels i.e., machine/component level, process level and software level, of interoperability can be occurred (Xu et al., 2020). At these various levels, different machines or components or processes, etc. not only from one organization but multiple organizations, must be able to communicate to process a certain manufacturing process, hence these different mechanisms must be easily integrated.

For predictive maintenance perspective, different machines, and related components as well as other related equipment within one product line or cross different organizations need to be monitored for the optimizing purposes of predictive maintenance. To do this, the different machine equipment tools must be integrated with the predictive maintenance system, with the support of different processes such as data collection and processing for predictive model, etc., as well as different smart devices such as IoT or sensor adapters, etc. This can be achieved by the ability of higher interoperability, particularly in the context of complex systems involved in Industry 4.0 (Xu et al., 2020).

Modularity: the flexibility of changing, expanding, and enhancing individual modules to fit new requirements in the existing manufacturing processes or to build new processes (Debevec et al., 2014; Zezulka et al., 2016). The different processes represent the functions of

[1] Sang et al. 2020. Predictive Maintenance in Industry 4.0. 10th International Conference on Information Systems and Technologies, ACM (Sang, Xu, de Vrieze, Bai and Pan, 2020)

[2] Sang et al. 2020. CAiSE 2020, Towards Predictive Maintenance for Flexible Manufacturing Using FIWARE (Sang, Xu, de Vrieze and Bai, 2020*b*)

[3] Sang et al. 2017. Simplifying Big Data Analytics Systems with a Reference Architecture. IFIP Advances in Information and Communication Technology (Sang et al., 2017)

[4] Sang et al. 2016. A reference architecture for big data systems. 10th International Conference on Software, Knowledge, Information Management & Applications (SKIMA) (Sang et al., 2016*a*)

the manufacturing processes which can also be referred as a set of services. These services should be accessible over the internet of thing by other systems. These services can be provided both internally within the same manufacturing unit and externally beyond the manufacturing unit's border.

In the context of predictive maintenance, different systems/processes/components e.g., big data analysis, machine/deep learning, etc., with data acquisition enablers such as sensor devices, adapters, etc., can be easily integrated or configured based on different business needs (Zezulka et al., 2016). Due to dynamic nature of Industry 4.0, different business needs or demands arise, for example new machine or component is required to be installed for meeting new product (Debevec et al., 2014). This process should be easily integrated or configured into existing system without significant effort, particularly for complex systems such as Industry 4.0 predictive maintenance system. Thus, supporting modularity is an important part of Industry 4.0 predictive maintenance, to facilitate the demands of dynamic and complex Industry 4.0 focusing environment.

Advanced capability: the ability to collect and analyze (both online and offline) manufacturing data such that the appropriate actions can be conducted effectively (Sang et al., 2021*a*; Zezulka et al., 2016). This enables effective controls of machines operations and maintenance. Furthermore, it facilitates the discovery of erroneous observations including possible manufacturing machine faults, wrong workers-machines interactions, and declines in production quality and reliability. Moreover, virtualization, the ability to monitor manufacturing processes such that virtual copies (digital twins) can be created for these processes. These virtual copies can be utilized as simulation and measurement environments for future enhancements of manufacturing processes (Debevec et al., 2014).

Besides, effective maintenance schedule optimization using advanced methods and techniques such as predictive models, etc., particularly for the consideration of minimal downtime and cost for multiple machines/components involved Industry 4.0, is a key aspect of capability which will lead to an optimal factory operation, reducing downtime and associated cost (Mobley, 2002).

Collaboration: the ability of different manufacturing systems to collaborate but also make decisions on their own e.g., decentralized optimizations such as maintenance schedule (Thoben et al., 2017; Zezulka et al., 2016). This requires the use of collaborative services, avoiding the use of centralized controls. Although, manufacturing systems can benefit from other facilities and systems like cloud manufacturing and fog manufacturing, they still need to be able to make their own decisions locally to effectively continue their operations via the collaborative network.

From Industry 4.0 predictive maintenance perspective, different collaborative manufacturing factories collaborate with other collaborative factories or partners. Each factory partner might have different configurations/operation of IoT systems or machine tools; however, these machine tools should be maintained at local level for an optimal state for the collaborative network. Any failure of the machine tools from a partner factory can huge impact i.e., downtime, cost, to the collaboration chain. Besides, the predictive maintenance services such as predictive model, maintenance scheduling, etc., can also be offered as a service to other collaborative factories, facilitating new monetization of optimized maintenance services which can assist in maintaining an effective maintenance management (Sang et al., 2021*a*,*b*; Zezulka et al., 2016).

Achieving these concepts is the key to an effective implementation and deployment of useful and highly beneficial Industry 4.0 predictive maintenance solutions (Mobley, 2002; Sang et al., 2021*a*; Zezulka et al., 2016). Thus, it is important to consider the specifics of these concepts in the design of these applications and find suitable techniques and technologies that can facilitate the seamless integration across all Industry 4.0 predictive maintenance applications components.

5.2 Predictive Maintenance Process and Predictive Maintenance Model for Industry 4.0

Based on the concepts, requirements and related work, the overall predictive maintenance process is constructed as presented in Figure 5.1 (a). The predictive maintenance process involves three core components including data acquisition, data process and prediction, and maintenance decision support. In section 5.2.1, *Data acquisition component* that is critical to operating the maintenance operation efficiently is discussed. The second process is the *data process and prediction component*. The collected data from various resources are processed for the optimization and detection such as failure to reduce impact on the manufacturing network. In Section 5.2.3.1, we present a predictive maintenance model for Industry 4.0 (more detail in Section 6), which can function for prediction the remaining useful life of machines/components. The second process provides a base for supporting maintenance decisions. The third component of the process is *maintenance decision support component*. This process deals with the general aspect of maintenance assisting an operator i.e. maintenance, engineer, etc., to act on an event prompting to perform a certain maintenance task. Different user interfaces or dashboards are also considered to aid the users in interacting

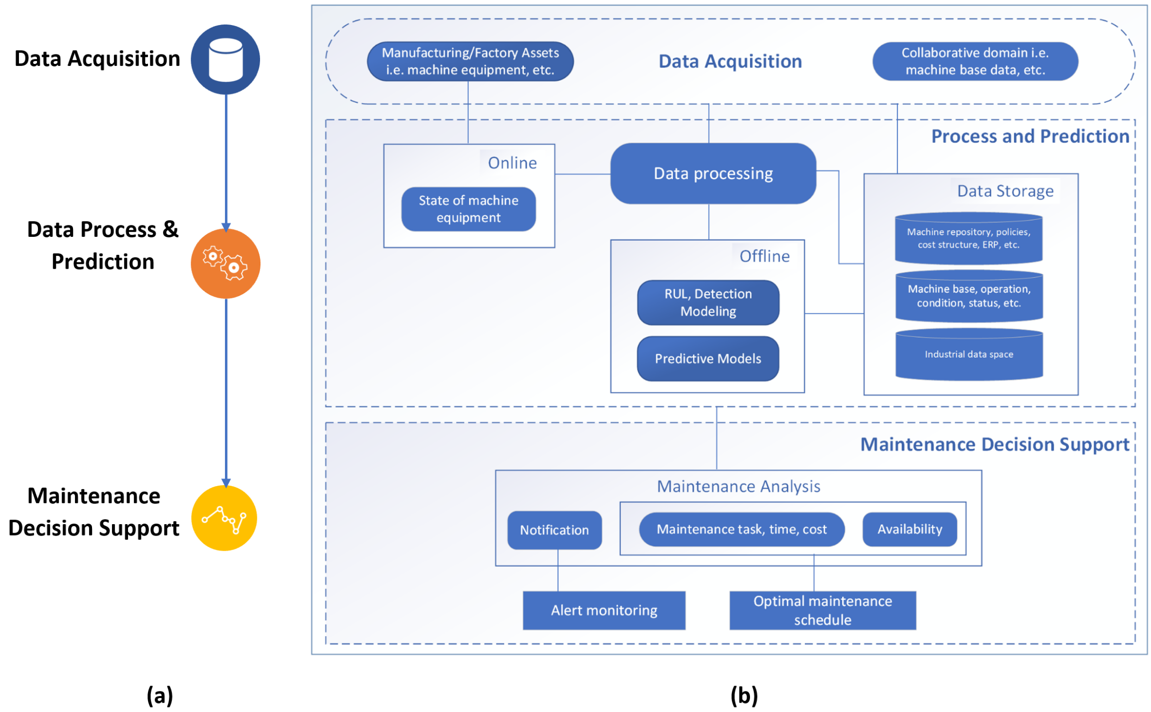


Fig. 5.1 Overall Predictive Maintenance Process and Framework (Sang et al., 2021*a*)

with the predictive maintenance. A detailed discussion of the supporting maintenance decision is discussed in Section 5.2.4.

5.2.1 Data Acquisition for Predictive Maintenance

The *data acquisition* in Figure 5.1 (b) for predictive maintenance concerns with collecting and processing data from the assets of the manufacturing enterprise. These assets refer to the entity or resource which is used for operating the factory operation at peak, efficiency, and the utilization to realize their failure can have a significant impact on the manufacturing chain. In this aspect, assets such as production machines, equipment, tools, industrial devices, and factory-related resources are considered.

Various data such as event, operation, and condition data, are being gathered during operation in a flexible manufacturing environment. For event data, it may include capturing data about the assets i.e. machine equipment tools with respect to the breakdown or failure event of the asset as well as the specific maintenance that was performed. In the case of operation data, it may involve collecting data of a certain process whereas the condition data may involve collecting data about the general condition i.e. health and measurements of the asset. Using different sensors, different signal data such as vibrations, temperature, pressure, can be collected as part of the general data acquisition i.e. event, condition (Sang, Xu, de Vrieze, Bai and Pan, 2020). In addition to acquisitioning various kinds of data from the factory machine equipment tools, and the different systems, processes of the collaborative partners are also being processed and collected (Sang et al., 2021*a*).

In general, the data acquisition relates to the online activities and processing in the complex manufacturing network. For predictive maintenance, the data generated by the operation of the different machine equipment tools of a flexible manufacturing product line should be collected. The online operating data acquisition allows synchronous data operation i.e. data to be collected, from the factory and its product line. The real-time data acquisition should reflect the status of the operating machine equipment tools. Using different data storages such as NoSQL, Hadoop HDFS, the acquisition data are processed and stored based on different business needs. The requirement may involve processing streaming data, staging processing, multi-dimensional or time series for analytics using Hadoop and NoSQL (Sang et al., 2021*a*; Sang, Xu, de Vrieze, Bai and Pan, 2020).

5.2.2 Data Model for Predictive Maintenance

Based on the various data that are processed, the collected data must be processed and stored in an efficient way for the utilization of different capabilities to support predictive maintenance. Maintenance planning requires information from different sources and storages that will assist in determining appropriate maintenance tasks (Sang et al., 2021*a*; Sang, Xu, de Vrieze, Bai and Pan, 2020). This requires the data to be efficiently captured and then made it available for the maintenance decision support. A data model that captures and reflects data from the resources and their dependencies assisted by the different data storages, processing and tools. This could lead to supporting the maintenance decision makers by making maintenance data available and thus facilitating an effective predictive maintenance.

A data model for predictive maintenance for Industry 4.0 is thus constructed in Figure 5.2 (Sang et al., 2021*a*). To support the different aspect e.g. extensibility of predictive maintenance, the data model is based on Fiware's context information model, enabling dynamic and extensible model. In Figure5.2, the model is illustrated with machine repository, maintenance repository, maintenance schedule, machine, component, machine base, process, and resource.

The *maintenance repository* concerns with related maintenance data including existing maintenance schedules. The *maintenance schedule* refers to the maintenance, machine, or resource related data. The *machine* stores data about the individual machine equipment tool including component(s), type, etc. The *machine base* is the machine specific data such as specification, configuration, etc., derived from the machine manufacturer. The

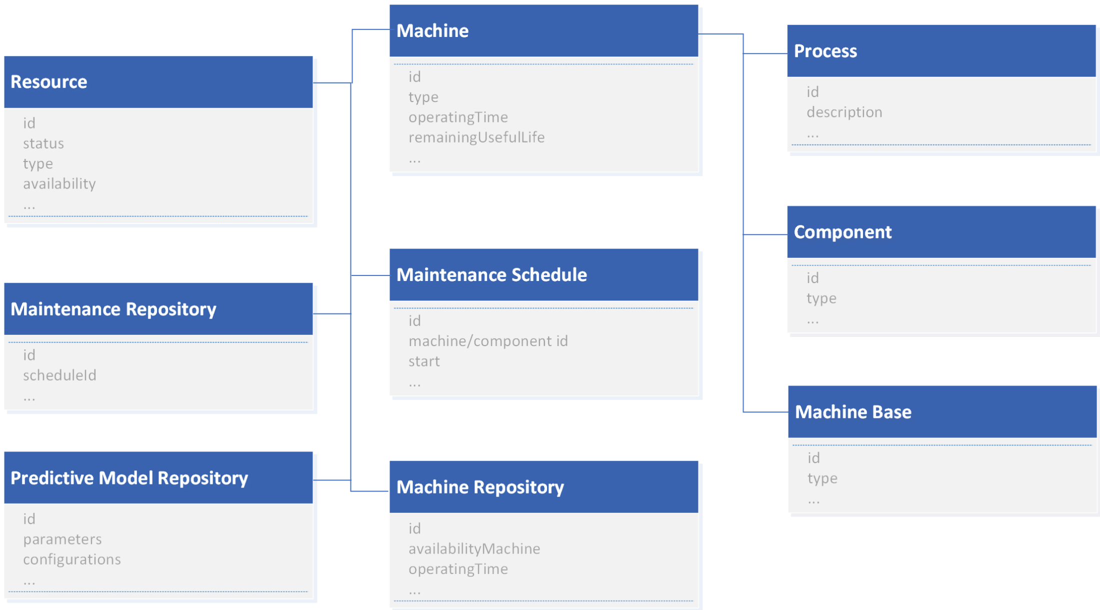


Fig. 5.2 Data Model for Predictive Maintenance for Industry 4.0 (Sang et al., 2021*a*)

specification of factory process for the machine equipment tools is facilitated by the *process*. The *predictive model repository* stores data related to the model, configuration, parameters, etc. for supporting modular predictive maintenance model.

The general data about factory machine equipment tools including their dependencies such as configuration/location/type of the machine component, maintenance engineer, etc., are supported by the *resource*. For maintenance decision support, these data are made available for the users such as engineers, technicians, in assisting their maintenance decision making. The model depicts the overall model which can also be extended upon requirements.

5.2.3 Data Process and Prediction

Using the data model, the general processing and modelling required for building a predictive model or acquisition information for analytics is supported the process and prediction in Figure 5.1 (b).

Data processing concerns with the general processes that are subject to producing the huge amount of data. This includes the manufacturing factory operation data including machine equipment tool data. Besides, manufacturing industry has data in related business information systems, such as ERP, Logistics, etc., as well as collaborative data such as product design, machine-based data that are facilitated by *Industrial Data Space (IDS)* (Fraunhofer, 2016) or other collaborative business systems. From the *data acquisition*, data are processed and stored in different *data storages* such as Hadoop HDFS, NoSQL, for different needs such as streaming data for specific NoSQL, staging processing, multi-dimensional or time series for analytics, etc.

Data must be processed and turned into actionable information for decision-making. In this context, different methods such as data cleaning, pre-processing, and reduction can be applied for various analyses and modelling. In the case of data cleaning, data operations such as format manipulation and missing value processing may be performed. As part of the data pre-processing, inconsistent or redundant data may be resolved. In most modelling cases, data reduction may be performed by transforming data into meaningful and simplified forms by means of feature or case collection (Sang et al., 2017, 2021*a*; Sang, Xu, de Vrieze, Bai and Pan, 2020).

Regarding data processing in the predictive maintenance framework in 5.1 (b), both *real-time (online) and offline* data are considered. In the case of *online*, real-time monitoring and notification are configured based on the operating condition of the machine equipment tool of the manufacturing factory. In this context, the status of the factory machines is processed to facilitate the functional aspect of the notification and monitoring.

In the case of *offline*, historical data and enterprise data collected from various processes and operations are utilized for developing different analytics solutions e.g. predictive model. Data are gathered from multiple sensors enabled machines/devices for predicting maintenance as part of the data acquisition process. This process is supported by the application of different adapters such as IoT adapters which are used for the integration of the lower level of the predictive maintenance and information level. In this way, both real-time and batch processes are processed by different ways e.g. real-time signal processing, vibration, etc. For data processing and modelling, data operations such as data pre-processing may be performed by cleaning, preparing, and formatting based on requirements, for building specific predictive models or general analytical functions (Sang et al., 2016*c*, 2017).

5.2.3.1 Predictive Model for Maintenance

In the context of building predictive models (i.e., predictive RUL model of process and prediction in Figure 5.1 (b)), models such as tool wear detections (i.e., worn, failure, degradation) and remaining useful life (RUL) are developed for deployment. The evaluated models can then be integrated with the platform for the prediction/detection of failure or degradation. Maintenance predictive models incorporating with related maintenance information provide a basis for determining predictive maintenance activity and schedule plans (Sang et al., 2021*a*).

Remaining useful life (RUL) is being recognized as an effective predictive maintenance since it can effectively estimate the end of life of a machine component (Sang et al., 2021*a*;

Sateesh Babu et al., 2016; Si et al., 2011; Tobon-Mejia et al., 2012; Zheng et al., 2017). In this context, maintenance based on RUL predictions can facilitates better optimizations such as in time acquiring of resources e.g. spare parts, engineer, etc., ultimately effective maintenance scheduling. The difference between high and medium accuracy may also mean significant savings in cases, where complex multiple machines/components are maintained, and maintenance costs are high. Predicted RUL and its corresponding horizon can be used for determining performance indicators or parameters that can lead to predicting the failure time.

In the context of Industry 4.0, resource dependency such as machines/components in a product line from one manufacturing organization to collaborative multiple organizations. The maintenance related data of each machine/component, condition, etc. need to be captured. For traditional manufacturing organization, the resource dependency may not be as critical as Industry 4.0 collaborative aspect, since the traditional organization does not need coordination or data outside its own organization, and that it can probably has its own capable resource. For an effective predictive maintenance, these resource dependencies must be considered, especially for scheduling. For developing the predictive RUL models, the machine equipment tools in factory operation should be considered (Sang et al., 2021*a*,*b*).

Manufacturing machine/equipment operational and condition data are collected via IoT sensor for developing RUL predictive models. These data are generally sequential sensor/time series data, and deep learning methods such as CNN, Long Short-Term Memory Network (LSTM) is effective in dealing with these data, compared with methods such as HMM, ARIMA, RNN (Baruah and Chinnam *, 2005; Bengio et al., 1994; Hochreiter and Schmidhuber, 1997; Martens and Sutskever, 2011). In this work, a hybrid approach, *Modular Predictive Maintenance Model using Hybrid Deep Learning Approach (MPMMHDLA)* i.e., different layers combination of the network is explored to handle both machine operation (sensor) data as well as condition data e.g. status of machine state, etc. There are different approaches for the predictive RUL models such as Zheng et al. (2017), Al-Dulaimi et al. (2019), Ren et al. (2018) which have use LSTM for the predicative models which are not designed in the context of Industry 4.0. We present the proposed *MPMMHDLA* in Chapter 6.

To build and train a predictive RUL model, manufacturing dataset that reflect the operation and condition of machine equipment tools can be used (Sang, Xu, de Vrieze and Bai, 2020*b*). In this aspect, the factory machine data such as machine operation and condition data are gathered during factory production. In this work, the manufacturing dataset from the FIRST industrial case as described in Chapter 6 is considered. Upon the development and evaluation of the predictive RUL model, it can be deployed and consumed via API on the platform. Based on business needs, the deployed model can then be set up for either online or offline use. The user e.g. maintenance engineer can trigger the RUL model and a list of potential machine components with the corresponding RUL values can be made available. Subsequently, the user may use the RULs as inputs (including other related information such as maintenance/machine data) for determining maintenance and related planning.

5.2.3.2 Maintenance Monitoring

One important aspect of maintenance (i.e., alert monitoring of maintenance decision support in Figure 5.1 (b)) is online (real-time) monitoring and notification. This relates to the general monitoring of the critical condition of the machine equipment tools that are involved in the factory operation. Critical and expensive machine equipment tools are considered as manufacturing assets. Any failure of these assets can have significant impact, resulting undesired downtime and cost. To prevent or avoid this, monitoring and detection of the critical condition of the machine equipment tools are considered as part of maintenance management (Mobley, 2002; Sang et al., 2021*a*).

Based on the characteristics of the asset acquiring maintenance, key indicators, and state information such as specific configurations or parameter settings, pressure level, etc., of the asset are established. Using the related to key indicators and state information, real-time data collected from the maintenance asset is processed for monitoring and determining qualified notification.

In the context of predictive maintenance framework in Figure 5.1 (b), different components such as interfaces, packages, databases, etc., can be integrated as requirements. In this way, the required maintenance alert rules e.g. detection of different thresholds such as failure stage, low-level of temperature or oil, can be configured as part of complex event processing for real-time analytics, connecting with stream processing via a message broker. Based on the nature of the alert notification, maintenance engineer can then take on appropriate actions.

5.2.4 Maintenance Decision Support

Maintenance Decision Support refers to the *Maintenance Decision Support* in Figure 5.1 (b) of the Overall Predictive Maintenance Process and Framework. Maintenance decision support covers the different options, applications, databases, and user interfaces that are used for maintenance analysis as depicted in Figure 5.3. In general, maintenance decision support facilitates the utilization of different applications including visualization of real-time monitoring and alert notification, schedule plan and general maintenance decision making.

At the maintenance analysis in Figure 5.3 (i.e., of maintenance decision support in Figure 5.1 (b)), the outcome of the analysis is derived from the predictive RUL models that

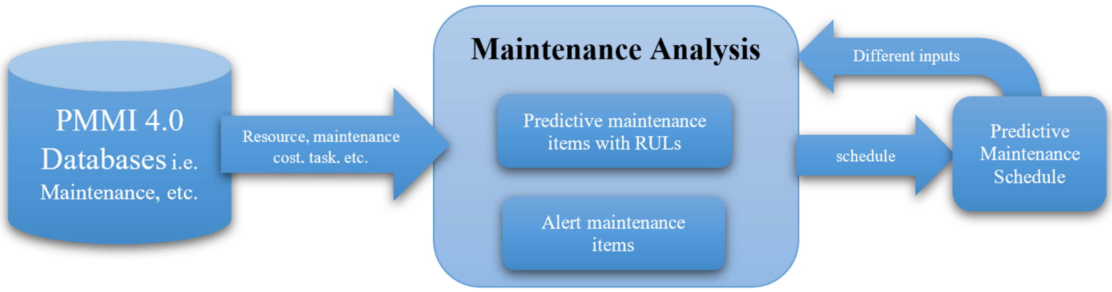


Fig. 5.3 PMMI 4.0 Maintenance Analysis for Maintenance Decision Support (Sang et al., 2021*a*)

forecasts future machine conditions. In this instance, the alert maintenance assets that are configured for the maintenance monitoring can be also be considered.

For maintenance analysis, the deployed predictive RUL model is triggered for generating the predicted RUL values of machines/components that are subject to potential failure. Using the forecast RUL values and related maintenance information such as maintenance cost, resource i.e. engineer, availability from the *PMMI 4.0* databases, analysis is performed and predictive maintenance schedule can be made, assisting decision making process as illustrated in Figure 5.3.

To support flexible maintenance, the dynamic nature of different inputs is considered. In this context, new RUL values of machines components, or different maintenance related information such as machine operation/condition, different maintenance time, etc., can be supported at the Maintenance Analysis. The information derived from the predictive maintenance schedule and factory maintenance related information available from the *PMMI 4.0* databases can be used against the operating machine equipment tools. Subsequently, appropriate maintenance decision i.e. appropriate maintenance tasks, schedule plan, etc. can be made.

We present a detailed discussion of maintenance decision support as part of predictive maintenance scheduling in Chapter 6.

5.3 Predictive Maintenance Model for Industry (PMMI) 4.0

From the realization of the concepts of Industry 4.0 in Section 5.1, key concept such as flexibility is critically important for Industry 4.0 predictive maintenance architecture. There are different architectures for predictive maintenance. Architecture approaches such as 5C

CPS architecture (Lee et al., 2015), IIRA (Lin et al., 2017), do not consider for the flexibility required for the modern industry to deal with dynamic changes and demands of complex manufacturing. They also lack the overall enterprise architecture required manufacturing predictive maintenance in the context of Industry 4.0. On the other hand, Reference Architecture Model Industry (RAMI) 4.0 offers a simplified architecture in complying with Industry 4.0 standards. Essentially, RAMI 4.0 simplifies Industry 4.0 with a three-dimensional model; hierarchy levels, functional layers and product lifecycle value stream (Zezulka et al., 2016). RAMI 4.0 offers a simplified coherent view that provides an understanding of complex systems and processes involved in complex Industry 4.0 (Sang, Xu, de Vrieze and Bai, 2020*a*; Sang, Xu, de Vrieze, Bai and Pan, 2020).

Moreover, a modular implementation platform is essential to operating advanced collaborative industry systems (Sang, Xu, de Vrieze, Bai and Pan, 2020). There are different implementation platforms for supporting predictive maintenance (Bagheri et al., 2015; Chiu et al., 2017; Lee et al., 2015; Schmidt and Wang, 2018; Wang, Gao and Yan, 2017). These approaches mainly deal with the aspect of data collection and analysis for predictive maintenance and however fail to address challenges such as modularity, interoperability which are critical to operating Industry 4.0 predictive maintenance. As such, FIWARE has the potential to offering a flexible solution. FIWARE is an open source framework and a service ecosystem composed of various components, described as Generic Enablers (GEs) (Fiware, n.d.*b*). The GEs can range from different IoT/smart devices, components, and services to big data analysis components for the development of different application solutions. Interoperability and modularity are the key aspects that the FIWARE platform promotes and supports. This offers the industries the ability to easily develop and integrate smart solution for different needs and processes with GE components in a modular manner (Fiware, n.d.*b*). In this work, FIWARE is thus adopted for several reasons such as flexibility, interoperability, supporting big data analytics, and by supporting open and industrial standard data model allowing the ease integration of different IoT smart devices, systems

Since Industry 4.0 focusing manufacturing is complex, and operates with several different machine including IoT devices, CNC machines, robots, the nature of data can be extremely frequent and highly huge. This requires not only supporting the integration of the different systems/machines but also supporting the ability to process big data is important for the proposed architecture. In this instance, the proposed solution should support the interactions among the different machines/components as well as the generated data for predictive maintenance by the characterization of end-to-end integration and processes, with different needs including the aspect of security, identity, privacy, etc.

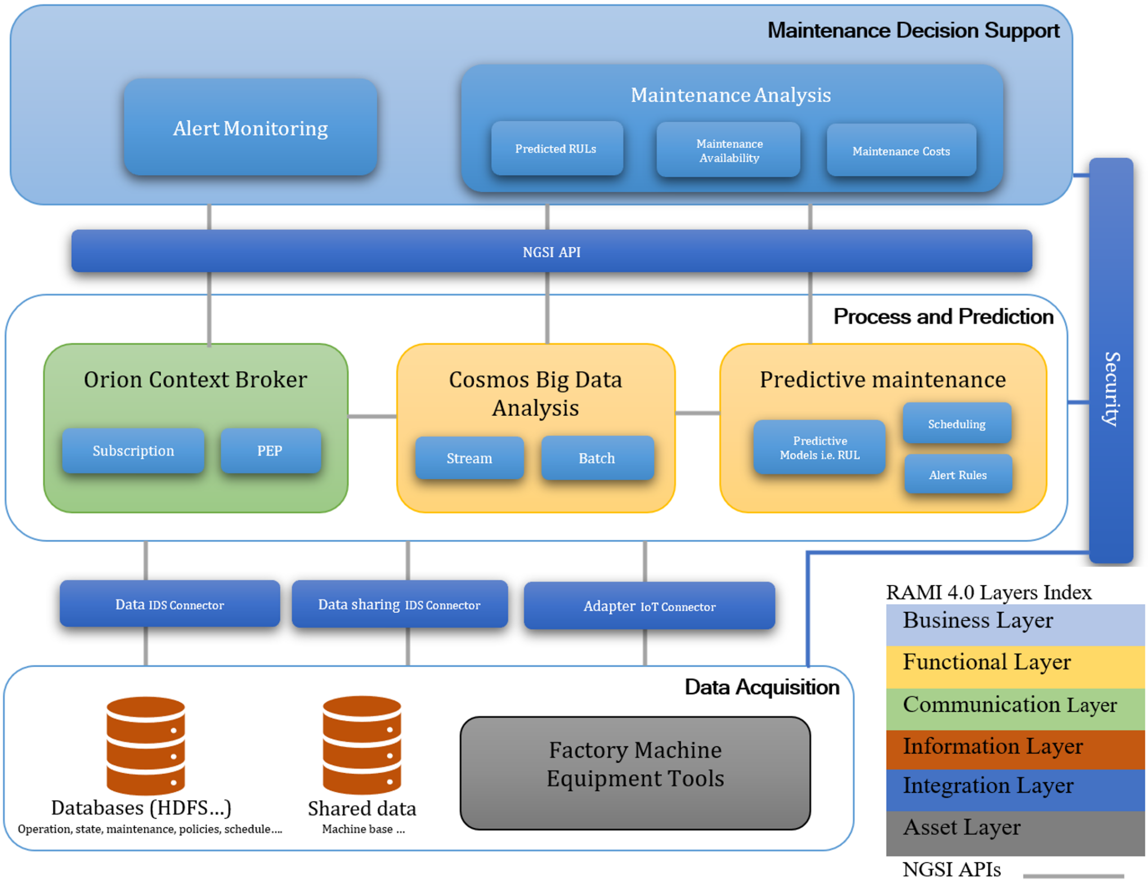


Fig. 5.4 PMMI 4.0 Architecture based on FIWARE and RAMI 4.0 (Sang et al., 2021*a*)

Based on the identified concepts of Industry 4.0 Predictive Maintenance in Section 5.1 as well as the requirements identified in the related work (i.e. Chapter 2), and the predictive maintenance process and framework described in Section 5.2, Predictive Maintenance Model for Industry 4.0 is designed adopting FIWARE and RAMI 4.0 as depicted Figure 5.4.

At the *Data Acquisition of PMMI 4.0* of PMMI 4.0 in Figure 5.4, the factory machine equipment tools, systems, and related processes are integrated with different adapters for manufacturing operation. The interaction of these machines, systems and processes generate data. These data are being collected and stored using different adapters and databases, representing the integration and information layer of RAMI 4.0.

Using PMMI 4.0 Industry 4.0 framework in Figure 5.1 (b), data from different sources such as sensors, smart machines, IoTs, as well as from different places such as Hadoop HDFS, NoSQL, and IDS, can be collected. IDS connector is implemented for the shared or collaborative data enabling transparency and traceability. In this context, manufacturing base data such as measurement, control data or product design data can be considered as the shared or collaborative data.

At the data acquisition of PMMI 4.0 framework in Figure 5.1 (b), the middleware, FIWARE Orion Context broker (the middle layer in Figure 5.4) represents the communication mechanism with different adapters and the related data sources and storages required for the platform. The Orion context broker connects with the different manufacturing assets including factory machine equipment tools and related processes, and data storage. The interaction is facilitated by different associated FIWARE's adapters (the low layer in Figure 5.4).

In practice, the Orion context broker acts as the middleware to facilitate the life cycle of the context information including registrations, updates, subscriptions, and queries via the NGSI REST API. For security enforcement, PEP Proxy is utilized for the interaction between the NGSI API and the different devices or systems, whereas IDS connectors are used for data access and control. To manage the aspect of security concerns such as privacy, encryption, Keyrock is applied with IDS connectors.

Based on the challenges faced by traditional data processing and tools for processing big data and related work (Sang et al., 2016*c*, 2017, 2021*a*; Sang, Xu, de Vrieze, Bai and Pan, 2020), the capability of advanced methods such as big data analytics is critically important for predictive maintenance.

The FIRWARE GE's Cosmos big data analytics thus is adopted at the *Process and Prediction of PMMI 4.0* in Figure 5.4, . To integrate Cosmos and different components required for functioning predictive maintenance, FIWARE's Orion context broker is employed. The Cosmos and Orion context broker represent the communication and functional layer of RAMI 4.0 in PMMI 4.0.

To support the different predictive maintenance functions on PMMI 4.0, predictive maintenance module is added. The predictive maintenance module holds the different capabilities such as predictive models, maintenance schedule, facilitating predictive maintenance services on the PMMI 4.0 platform in Figure 5.4.

The predictive maintenance module is supported by the different processing and tools of the adopted FIWARE's Cosmos Big Data Generic Enabler for PMMI 4.0 architecture in Figure 5.4. In this way, the capability of advanced big data analytics such as streaming and batch data processing, along with different available IoT or device adapters, are integrated. Hence, the platform can handle the required Big Data analysis of batch or stream data that can come from the data acquisition i.e. factory machine equipment tools. In the process instance, different components such as Hadoop engine, an authentications generator based on NGSI API and a connector to the FIWARE Orion context broker are employed (Fiware, n.d.*a*).

At Cosmos Big Data GE of PMMI 4.0 in Figure 5.4, data can be processed via Hadoop command line interface such as shell. Alternatively, Telefonica's SSH File Transfer Protocol (SFTP) server can be used by processing the data into HDFS. SFTP is supported by Cosmos Big Data GE via an interface that facilitates the transfer files into PMMI 4.0 platform (Fiware, n.d.*a*; Hadoop, n.d.). From the data acquisition, data can be processed by MapReduce, and the results can then be consumed via HDFS for access i.e. applications, users. In this instance, the Orion Context broker acts the middleware as well as connects with HDFS and other components. The access of the results can be made to other applications or users via the NGSI API.

Since PMMI 4.0 supports flexible integration, different big data enabled components such as Cygnus for data persistence, STH Comet, can be integrated into PMMI 4.0 based on different business requirements. In this way, PMMI 4.0 supports flexible integration as a plug-in/plug-out option, allowing different processing such as real-time or batch data processing, which can be integrated with different functions including maintenance monitoring.

At the *Maintenance Decision Support of PMMI 4.0* in Figure 5.4, providing the interface to monitoring or interactively configuring the maintenance schedule using different visualization of maintenance analysis. The deployed predictive RUL model is triggered for generating the predicted RUL values of machines/components that are subject to potential failure. Using the forecast RUL values and related maintenance information such as maintenance cost, resource i.e. engineer, availability from the platform databases, analysis is performed. In this way, a list of potential machine components for corresponding RUL values as well as related maintenance data can be used as inputs and subsequent predictive maintenance schedule can be made, assisting maintenance decision making process.

For maintenance information, related information is retrieved from the data storage which is accommodated by the proposed data model in Figure 5.2. To assist in making maintenance decision, the availability of different related maintenance information about manufacturing assets i.e., machine equipment tools, is essential. In this aspect, different maintenance asset can be defined for different manufacturing context. In the industrial case presented in this work, the key maintenance information regarding the underlying assets defined for maintenance assets includes both single machine, component as well as a group of machines/components within the product line. FIWARE GE's components such as Grafana or Hive for ad hoc query can be easily integrated with the platform for different user interfaces.

5.4 PMMI 4.0 Implementation Environment, Evaluation and Analysis

In this section, we show the applicability and effectiveness of the proposed PMMI 4.0 using real world industrial cases of the FIRST project. We explain the PMMI 4.0 implementation environment for FIRST manufacturing application case (i.e., Chapter 3) in Section 5.4.1. The evaluation of the implementation for PMMI 4.0 and the application case is provided in Section 5.4.2 and lastly, comparison between PMMI 4.0 and existing architecture solutions are presented in Section 5.4.3.

5.4.1 FIRST Manufacturing Application Case of PMMI 4.0

To demonstrate the applicability of our proposed solution, PMMI 4.0 in Figure 5.4 and the Predictive Maintenance Process in Figure 5.1 are implemented for FIRST manufacturing application case (i.e., Chapter 3) as shown in Figure 5.5 using key components of FIWARE enabling Big Data Analytics with the predictive services such as predictive models, maintenance analysis.

At the *Data Acquisition* in Figure 5.5, the different factory machine equipment tools, devices, systems, and related processes are integrated via related adapters for manufacturing operation. The interaction of these different machine tools and processes are enabled by the Orion context broker. The different data collection and processing are accommodated by the platform databases utilizing the proposed data model in Figure 5.2. For seamless connecting, managing, and gathering data of IoT devices in this case, the FIWARE generic enablers such as IoT Agent and NGSI API for e.g. complex real-time processing are configured and connected with the context broker.

At the *Data Process and Prediction* context in Figure 5.5, different data processing and modelling for functioning predictive maintenance services are considered. To support the predictive maintenance module i.e. different functions of predictive maintenance, FIWARE generic enablers based on business needs are integrated. In this instance, the FIWARE's Cosmos big analysis i.e. Cosmos Spark for streaming with corresponding data storages such as HDSF, CraftDB (i.e. time series facilitated by QuantumLeap) is integrated for supporting the capability of big data analytics. For the predictive maintenance module, predictive maintenance services such as Predictive RUL Model, *MPMMHDLA* (i.e. chapter 6) and *PMS4MMC* (i.e. chapter 7) are built and integrated.

The Orion context broker facilitates the interactions and communications between the different components and processes via NGSI APIs. To manage the aspect of security, the

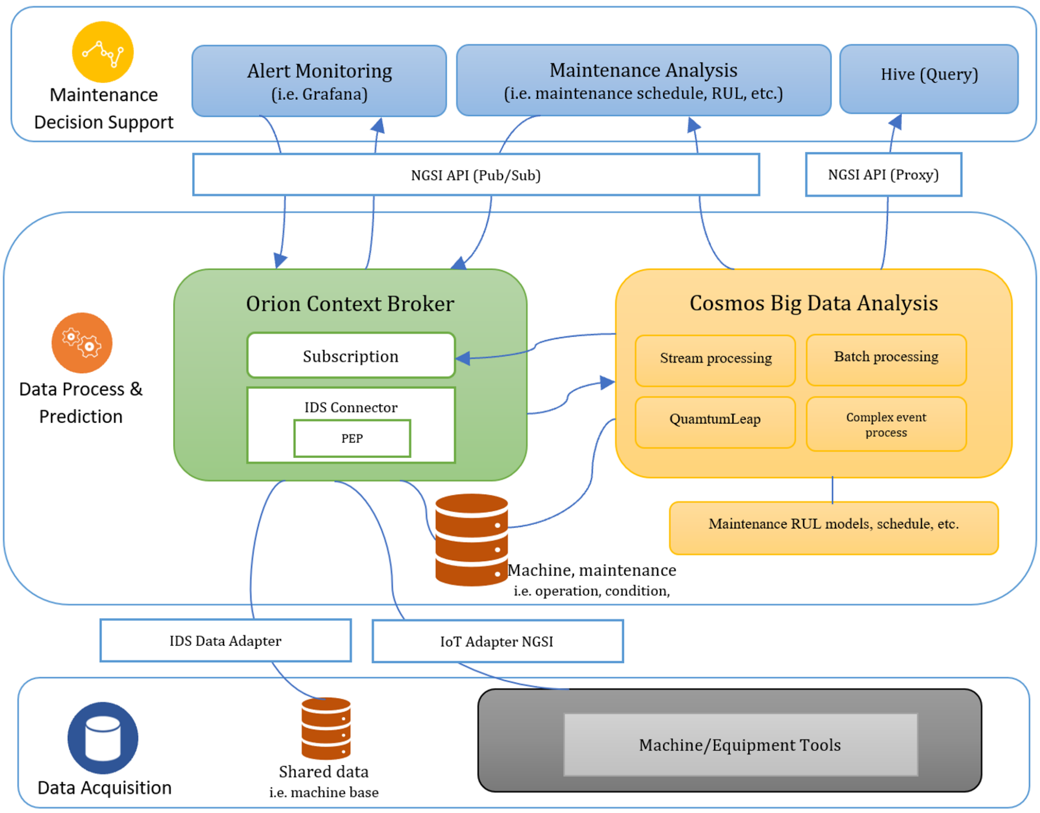


Fig. 5.5 PMMI 4.0 Implementation for FIRST Manufacturing Predictive Maintenance Case (Sang et al., 2021*a*)

platform is integrated with PEP Proxy, Keyrock over the communications, accesses and APIs. To support the data storages i.e. operation/maintenance data, required for the platform, databases such as HDSF, CraftDB, are integrated with PMMI 4.0 for the case (Fiware, n.d.*a*,n,n; Hadoop, n.d.).

For the predictive maintenance module, the Python Kera Tensor Flow Backend (Goodfellow et al., 2016) for Predictive RUL Model, *MPMMHDLA* (i.e. chapter 6) and predictive maintenance scheduling *PMS4MMC* (i.e. chapter 7) are deployed and consumed via the NGSI API.

In the context of *Maintenance Decision Support* in Figure 5.5, the Maintenance Analysis is facilitated by Grafana (e.g. alert monitoring), Hive (for ad hoc query) (i.e. Grafana offers to view or notify real-time data generated by machine equipment utilizing the QuantumLeap and complex event processing, and Hive (SQL) query is supported for ad hoc query within the big data analytics module), and Angular frontend application for accessing the predictive maintenance services (i.e. predictive RUL model and PMS4MMC scheduling). Moreover, information about maintenance, machine equipment stored in the maintenance and machine repository proposed in the data model in Figure 5.2 is available at the Maintenance Analysis. This includes, the maintenance type, task and associated cost, availability of the resource such as engineer, etc., the design of each machine and its configuration capability such as the workpiece, etc., and the information related to the available machines and their parameters.

For maintenance analysis, the deployed predictive RUL model is triggered for generating the predicted RUL values of machines/components that are subject to potential failure. Using the forecast RUL values and related maintenance information such as maintenance cost, resource i.e. engineer, availability from the *PMMI 4.0* databases, analysis is performed and predictive maintenance schedule can be made, assisting decision making process.

Based on the related work and concepts of Industry 4.0 predictive maintenance in Section 5.1, PMMI 4.0 is designed for supporting flexibility. This allows flexible integration of different or new business process that can be adapted into existing services or set up upon requirements. In this context, the integration of different FIWARE generic enablers such as Knowage or third-party software or commercial open source tools can easily be achieved over the platform. This may offer a potential solution for meeting with dynamic requirements and different business needs for analytics (Fiware, n.d.*b*; Jason, n.d.). To achieve better scalability, FIWARE container virtualization using container images is employed (Sang, Xu, de Vrieze and Bai, 2020*b*).

In the next two chapters (i.e. chapter 6 and chapter 7), we present the detailed solution and verification of PMMI 4.0 (i.e. predictive maintenance model in chapter 6) and PMS4MMC (i.e. predictive maintenance scheduling in chapter 7) using the FIRST implementation setting.

5.4.2 Evaluation of PMMI 4.0 and the Application Case

In Industry 4.0 context, collaborative manufacturing industries face different challenges due to the complexity and dynamic nature of the industry collaboration environment (Thoben et al., 2017). Advanced manufacturing such as the described case is complex, and involves advanced operating machines, smart sensors, and robots running on the shop floor as well as a network of collaborations including collaborative business processes e.g. different systems, multiple collaborative partners such as suppliers, manufacturers, designers, customer, etc. To overcome the challenges, a concrete, flexible architecture platform for predictive maintenance supporting modularity, interoperability, and advanced capabilities such as big data, predictive analytics, is essentially important.

PMMI 4.0 is evaluated, particularly in its *applicability and effectiveness (See Relevance and Rigor in Section 4.4), modularity, and interoperability (See Section 5.1.1, Section 5.1)* in the FIRST project real world industrial setting. As Industry 4.0 industries are complex, an architecture platform solution must be flexible enough to adapt to different demands or requirements (Koren et al., 2018; Sang, Xu, de Vrieze and Bai, 2020*a*; Thoben et al., 2017). Thus, the aspect of *applicability, effectiveness, modularity, and interoperability* are critical important for the validation of one solution adhering Industry 4.0 standards and application as previously described in Section 5.4. In this aspect, the evaluation of the proposed PMMI 4.0 is done using real-world industrial case of the FIRST project.

The *applicability* refers to the ability that the solution can fit real world environments whereas the *effectiveness* refers to the degree of requirements e.g., key functions of predictive maintenance services, etc., that can be easily integrated for business i.e., maintenance cases. To respond to dynamic changes or requirements of Industry 4.0 (Koren et al., 2018; Thoben et al., 2017), the capabilities of the architecture platform solution must be able to adapt to new requirements with high interoperability. The aspect *modularity* concerns with easily adapting and configuring new business changes or requirements whereas the *interoperability* is the ability to easily integrate with different processes/systems at different levels e.g., machine level, process level, etc.

A comparison analysis with related works using these key elements: *applicability, effectiveness, modularity, and interoperability* is provided in the next section 5.4.3.

5.4.2.1 Applicability of PMMI 4.0 for Industry 4.0 Predictive Maintenance

Designing an Industry 4.0 predictive maintenance requires the understanding of the industry operations, partners, communication, and the underlying technologies. 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 are essential to designing predictive maintenance. 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 architecture have been explored in (Chiu et al., 2017; Lee et al., 2015; Schmidt and Wang, 2018; Wang, Gao and Yan, 2017). The most recent approaches such as Lee et al. (2015), Bousdekis et al. (2019), recognized the aspect of RAMI 4.0 and Industry 4.0, and however they failed to address critical factors such as flexibility, modularity, interoperability which are essential to developing flexible Industry 4.0 predictive maintenance architecture platform. The complexity of the industry in our approach can be simplified by the instantiation of RAMI 4.0 as shown in Figure 5.4 and discussed in Section 5.3. *Our proposed solution based on RAMI 4.0* in Figure 5.4 enables better understanding about the interaction of complex processes and components via a high-level view.

Industry 4.0 systems operate with a combination of different systems, machine equipment tools, etc., not only one factory but also across different factories network, and these different systems work together to fulfil an overall business goal (Sang et al., 2021*b*). The different systems coordinate different processes of the manufacturing process or depend on the data generated in other systems. Replacing or configuring a machine equipment tool should not lead to additional engineering effort being needed for adaptation (Koren et al., 2018; Sang, Xu, de Vrieze and Bai, 2020*a*). Hence, system architectures should integrate the collaborative machines/tools/systems/processes etc., modularly. In this aspect, the different collaborative machines/tools/systems/processes etc., should communicate with each other over standardized interfaces for the required business need or process, reducing the necessity for point-to-point interfaces.

5.4.2.2 Modularity of PMMI 4.0

Modularity is the basis for Industry 4.0 focusing manufacturing systems (Sang, Xu, de Vrieze, Bai and Pan, 2020). Modularity features satisfy the dynamic demands and collaborations in Industry 4.0 era. In our approach for designing PMMI 4.0, *flexibility and modularity* are achieved by the adoption of the FIWARE framework, an implementation of RAMI 4.0 architecture. Thus, the proposed predictive maintenance architecture platform in Figure 5.4 supports the flexibility and interoperability needed for Industry 4.0 predictive maintenance. Using FIWARE in our solution, different data adapters of FIWARE adapters to connect different smart machines, robots, IoT sensors, CPS, and other legacy systems such as ERP, CRM, and SCM provide the interoperability among data, services, and processes, compared with existing approaches such as Lee et al. (2015), Lin et al. (2017) in which they fail to address the aspect of modularity that is essentially important in dealing with complex and dynamic Industry 4.0 systems.

In relation to PMMI 4.0 implementation with the application case in Section 5.4, the three core components i.e., data acquisition, data processing and prediction, and maintenance decision support in Figure 5.5, can be extended as business needs at different levels. For example, new machine at the *data acquisition*, can be integrated or configured for new requirement which then can be connected/integrated with the big data processing (at data process and prediction) and context broker via data adapter, and then information e.g., for maintenance analytics can be made available at the *maintenance decision support* via NGSI API.

This *end-to-end* process can be easily integrated since PMMI 4.0 is designed to be flexible architecture platform that adopts flexible FIWARE framework, supporting modular platform and industrial standards i.e., data model in Figure 5.2, along with different generic enablers components including third party software or packages. Besides, our proposed PMMI 4.0 solution facilitated by RAMI 4.0 architecture offers the design architecture of the complex process in a simplified manner which supports Industry 4.0 standards as implemented case i.e., Figure 5.5 at Section 5.4. In the same ways, different business requirements or changes can be easily integrated or adapted into existing modules/processes/components using the proposed PMMI 4.0 as implemented in Section 5.4. This demonstrates the modularity as well as applicability and effectiveness of our solution. Furthermore, the application of effective predictive maintenance enabled by the big data analytics component not only reduces impacts such as downtime, costs, etc. but could potentially facilitate new innovations and sustainability aspect in the collaborative manufacturing chain.

5.4.2.3 Interoperability of PMMI 4.0

The *interoperation* of collaborative machines/tools/systems/processes etc., requires data to be processed which is communicated i.e., sent, and received by various systems or processes. These systems or processes can come from different collaborative partners such as manufacturers, suppliers, etc., leading to a heterogeneous amalgamation of systems or processes. An industrial common information model which defines a common understanding of the data is required to allow communication between each collaborative system/machine/process and the architecture.

Regarding PMMI 4.0, it supports *interoperability* by providing Industry 4.0 standard information model facilitated by the adoption of FIWARE's information model which is derived from various industrial standards and models at different levels, machine or process or system level, for supporting modular and flexible industrial collaboration (Fiware, n.d.*b*; Sang et al., 2021*b*). This leads to enabling the seamless integration of different machines/systems/processes for business i.e., manufacturing chain needs/changes. For the manufacturing case in Chapter 3, it operates with various expensive machine equipment tools such as CNC machines, robots, etc., as well as different processes and information systems including collaborative partners such as manufacturers, suppliers, etc. The different systems/machines/processes require different interfaces for operating with the factory systems as well as integrating the big data enabled predictive maintenance services such as data collection, processing, predictive model, maintenance scheduling, etc. For example, at the implementation level, PMMI 4.0 supported by FIWARE, facilitate the ability to easily integrate different systems or components i.e., FIWARE's GE (Generic Enabler) or third-party software, etc., as a plug in/out. For example, the Cosmos big data component with different data or IoT adapters via the context broker enables integrating big data analytics solutions i.e., predictive maintenance, etc. Existing approaches such as Lee et al. (2015), Lin et al. (2017) focus on the overall architecture design but do not address the fundamental key components such as interoperability, modularity which are essential aspect of operating Industry 4.0 systems.

The adoption of FIWARE in the proposed PMMI 4.0 platform further delivers 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 platform of FIWARE enables the easy integration of different components as pluggable elements. On the other hand, FIWARE implementation is based on an event-driven approach which can pose challenges such as increased complexity, security risks.

5.4.2.4 Advanced capability of PMMI 4.0

One key challenge for Industry 4.0 manufacturing is to *design and develop embedded services assist in a flexible way* supporting the effective management of machine equipment tools by reducing downtimes and costs (Brewka, 1996; Lee et al., 2014; Mobley, 2002; Sang et al., 2021*b*; Sang, Xu, de Vrieze and Bai, 2020*a*; Zonta et al., 2020). Based on the challenge and the concepts described in Section 5.1, we propose and present a predictive maintenance model for Industry 4.0. The proposed solution supports different predictive maintenance services including the proposed predictive maintenance scheduling for multiple machine components (i.e. part of the maintenance decision support in Figure 5.3 and the detailed solution in Chapter 7) by taking into advantage of machine data such as operation, condition, and maintenance data. Through the application of the modular FIWARE framework on PMMI 4.0, big data analytics on new data streams in the connected machine equipment tools the approach benefits from deep algorithms and optimizations to perform predictive maintenance.

Essentially, one architecture platform solution should address the aspect of *advanced capabilities* such as big data analytics, predictive model, optimized maintenance schemes, etc., which are the key enablers of operating Industry 4.0 organizations effectively (Koren et al., 2018; Sang et al., 2017; Sang, Xu, de Vrieze and Bai, 2020*a*; Thoben et al., 2017). Regarding our solution, we design the key enablers of Industry 4.0 predictive maintenance into three different components: *data acquisition, data process and prediction, and maintenance decision support* as shown in Figure 5.4. These components are empowered by the capability of big data processing and analytics which are facilitated by the adoption of flexible FIWARE framework which also supports a combination of different components/software/packages from its Generic Enablers components or third-party software. In the case of existing approaches such as Lee et al. (2015), Lin et al. (2017), they do not offer the key components or processes that can assist in implementing advanced capabilities such as predictive maintenance services, etc. since these capabilities i.e., big data enabled predictive maintenance services, etc., are critically important for complex Industry 4.0 organizations in dealing with downtime and cost (Mobley, 2002; Sang et al., 2021*b*).

5.4.2.5 Effectiveness of PMMI 4.0

In the case of the application case as described in Chapter 3, the manufacturing process i.e., collaborative business processes/systems/machines, etc., becomes more and more complex. And it is hard to effectively identify the problems arising in the manufacturing process by the traditional approach (Sang et al., 2021*b*). These potential maintenance problems in modern manufacturing can be detected by the application of big data analytics. Using our PMMI 4.0, 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 i.e., alert morning of maintenance decision supported in Figure 5.5. Previously, most of the data generated by the production machines in the application case are simply stored in the different databases or the log files in different machines. These data ultimately have not been explored for analytics. A coherent predictive maintenance platform allows the abilities to easily integrate data from different machines, devices, and systems as well as to easily deploy IoT/smart device sensors for monitoring. At the implemented PMMI 4.0 in Section 5.4 enables predictive maintenance platform for the manufacturing case, the maintenance services are embedded and optimized with operation and production processes which could achieve optimization for maintenances as implemented and shown in Figure 5.5. This demonstrates the effectiveness and applicability of our solution for real world application uses.

In the context of predictive maintenance for Industry 4.0, as previously discussed, existing solutions such as Lee et al. (2015), Bagheri et al. (2015), Chiu et al. (2017), Wang, Gao and Yan (2017), Schmidt et al. (2017) do not consider the aspect of flexibility or modular platform, which is essential to operating complex and dynamic Industry 4.0 systems. Our solution, PMMI 4.0, however fits well with the FIRST industrial application case in achieving modular architecture platform with high interoperability, and capabilities such as Big Data Analytics (Cosmos GE) component as described in Section 5.4 and Figure 5.5. In this context, the predictive maintenance module includes the different maintenance services including predictive model and scheduling. The module supported by FIWARE's big data analysis, is embedded into PMMI 4.0 for supporting the different services for maintenance. New predictive models or maintenance services can then be integrated or adapted into the existing module or processes to meet different needs. To manage the aspect of security, FIWARE generic enablers such as Keyrock, Wilma (Fiware, n.d.*b*) or third-party tools are considered and integrated as required. On the other hand, FIWARE implementation uses the core context broker which is based on event-driven approach. Challenges such as complexity, security risks should appropriately be managed. Using similar or different case, further validation of PMMI 4.0 may be gained by using the offers of commercial platforms such as Azure, Amazon.

In this work, we focus on Industry 4.0 complex manufacturing and the proposed solution PMMI 4.0 is verified using FIRST manufacturing cases. Since big data analytic become one key asset to organization (Porter and Heppelmann, 2014; Sang et al., 2016*a*, 2017; Zezulka et al., 2016), PMMI 4.0 may well be applied to other industries for maintenance services since PMMI 4.0 supports the capability of big data analytics enabled predictive maintenance. In this instance, PMMI 4.0 can be adopted for a data centre organization. The company's asset such as hard drive can be integrated using the FIWARE's generic adapter that is linked with the Cosmos Big Data Analytics component for stream processing, allowing maintenance purposes such as monitoring (Fiware, n.d.*b*; Jason, n.d.). Using the sensor data from the hard drive system, predictive maintenance model such as RUL can be built, deployed, and configured for maintenance services. Using the big data analytics and predictive maintenance services such as RUL, maintenance analysis can be performed, enabling optimal predictive maintenance schedule can appropriately be produced. Similar adoptions may well be applied to other industries such as smart cities, buildings e.g. electricity station or traffic light with sensor monitoring and maintenance purposes.

5.4.3 Comparison with existing architecture solutions

To evaluate the applicability and effectiveness of our proposed PMMI 4.0 solution (i.e. Section 5.3), we compare our solution with some of the most recent works in the field of manufacturing in the research community. We utilize the key elements that are essential to operating Industry 4.0 predictive maintenance as previously discussed in the evaluation of our solution at Section 5.4.2 as well as the key concepts which is described in Section 5.1. The related works include:

A Lee et al. (2015) proposes 5C architecture for the realization of cyber-physical systems (CPS) with the levels smart connection (I), data-to-information conversion (II), cyber (III), cognition (IV), and configuration (V). The architecture serves as a guideline for implementations and realizations of CPS within one organization. It provides a technology-neutral starting point for I4.0 architectures and CPS.

B Industrial Internet Reference Architecture (IIRA) is an abstract reference model for dealing with industrial internet of thing systems (Lin et al., 2017). It specifies an Industrial Internet Architecture Framework comprising viewpoints and concerns to aid in the development, documentation, and communication of the IIRA.

C ARUM project (Leitao et al., 2013) is an agent-based architecture with an enterprise service bus (ESB) acting as middleware between the different systems. Legacy devices are incorporated using gateways. An ontology embedded in the middleware contributes to a common understanding of information.

D ESB-based architecture (Hufnagel and Vogel-Heuser, 2015) captures data integration from various heterogeneous sources using an ESB-based architecture. The architecture uses adapters to translate between data formats, thereby enabling the incorporation of legacy devices. A common information model with mapping rules that parametrize the data adapters serves to create a common understanding.

E Line Information System Architecture (Theorin et al., 2017) uses an ESB for a prototypical implementation. The aim of the approach is to allow a flexible data integration in factories. A common information model and data adapters translate between the different systems.

F The SOCRADES architecture (Karnouskos et al., 2009) uses gateways and mediators for the integration of legacy devices. Web services facilitate interoperability and loose coupling between the systems. The discovery of services and their orchestration play an important role.

Table 5.1 Comparison between the proposed solution PMMI 4.0 and some existing architecture solutions for Industry 4.0 predictive maintenance

	Approach	Modularity	Interoperability	Applicability	Effectiveness
A	5C architecture (Lee et al., 2015)	L	L	L	L
B	IIRA abstract architecture (Lin et al., 2017)	x	x	L	L
C	ARUM agent based architecture (Leitao et al., 2013)	x	L	x	x
D	ESB-based architecture (Hufnagel and Vogel-Heuser, 2015)	x	L	x	x
E	Line Information System Architecture ESB-based (Theorin et al., 2017)	x	x	x	x
F	SOCRADES architecture SOA-based (Karnouskos et al., 2009)	x	x	x	x
G	Arrowhead project cloud-based SOA framework (Delsing, 2017)	L	L	L	L
H	Semantic cloud framework (Schmidt et al., 2017)	L	L	L	L
I	Manufacturing cell-based maintenance (Chiu et al., 2017)	L	L	L	L
J	A unified predictive maintenance platform (Bousdekis et al., 2019)	L	L	L	L
	Our Solution – PMMI 4.0	S	S	S	S

Modularity	To easily add/configure systems/processes/machines/tools based on business features/needs
Interoperability	To easily integrate with different systems/processes/machines/tools, etc.
Applicability	Feasible for Industry 4.0 focusing context
Effectiveness	Application for busines cases i.e., predictive maintenance services, etc.
L	Limited or only some features are supported for Industry 4.0 based predictive maintenance
S	Support for Industry 4.0 based predictive maintenance
x	No support or applicable for Industry 4.0

G The Arrowhead project (Delsing, 2017) provides a framework for the cloud-based interaction of systems. It closely follows SOA principles and considers data exchange across organizational borders. Additionally, it enables real-time capable communication if necessary.

H A semantic cloud framework for predictive maintenance was proposed by Schmidt et al. (2017). To improve maintenance decision support, data integration of different types such as condition monitoring, inspection and process data, data from a variety of sources can appear in different formats and with different sampling rates are considered. It highlights those challenges and presents a semantic framework for data collection, synthesis and knowledge sharing in a Cloud environment for predictive maintenance.

I Chiu et al. (2017) presents a predictive maintenance focusing on a manufacturing cell (CPS), which mostly deals with monitoring the equipment tools. A factory-wide intelligent predictive maintenance system by applying cyber-physical agent and advanced manufacturing cloud of Things according to Industry 4.0, predictive maintenance functions, and health index hierarchy to supervise factory-wide equipment maintenance.

J A unified predictive maintenance software architecture platform (Bousdekis et al., 2019). Different processes and functions are designed according to RAMI 4.0. The integration of enterprise systems including legacy systems are being focused to develop analytics solution for maintenance. It is applied to a real manufacturing scenario from the steel industry.

Table 5.1 shows the comparison between our solution PMMI 4.0 and some existing architecture solutions in the field of manufacturing. In relation to modularity, our solution

PMMI 4.0 is the only solution that supports modular architecture platform, and approach ***A, H, I and J*** in Table 5.1 only support for limited features since approach ***A*** focuses on cyber physical systems and its integration with manufacturing systems whereas approach ***I*** deals with manufacturing cells in the context of Industry 4.0, approach ***J*** concerns with the design aspect according to RAMI 4.0, and approach ***H*** focuses on the utilization of cloud framework in a semantic approach. These approaches also lack the consideration for other different systems i.e., CPS, robots, etc., information systems or collaborative business processes involved in Industry 4.0 manufacturing chain. Similarly, other approaches fail to address the aspect of ***modularity***, especially in dealing with complex Industry 4.0 systems. To effectively manage the dynamic changes or demands of Industry 4.0, a coherent Industry 4.0 predictive maintenance architecture platform must support the ability to easily integrate new processes/systems/machines or adapt existing processes or systems without significant effort. In this aspect, our solution PMMI 4.0 is verified using the FIRST project industrial case in Section 5.4.

Regarding the ***interoperability***, most approaches such as ***A, C, D, H, and I*** in Table 5.1 focus on specific domain, for example, both approach ***A and I*** focus on the integration of CPSs but do not consider the wider aspect of the enterprise systems, processes, etc., while approach ***C, D and H*** focus the enterprise integration i.e., enterprise service bus however ignore Industry 4.0 systems such as CPS, IoT, etc. On the other hand, our proposed solution facilitates high interoperability for Industry 4.0 systems by adopting modular FIWARE's components such as data adapter which is accommodated by the industrial standardized information model with the support of different interfaces from machine level to system or process. Moreover, three core different components such as data acquisition, data process and prediction and maintenance decision support, utilizing RAMI 4.0 architecture of PMMI 4.0 leads to a simplified view of complex systems/processes, etc., thus adhering Industry 4.0 standards and enabling better management and implementation of complex systems. Thus, our architecture is more general and comply with Industry 4.0 than other existing solutions, which offers high interoperable Industry 4.0 architecture platform for predictive maintenance.

In respect to ***applicability*** for Industry 4.0, approaches such ***A, B, H, I and J*** in Table 5.1 partially deal with Industry 4.0 focusing context and use case. Regarding approaches ***A and I***, both focuses on CPS in a manufacturing context whereas approaches ***H and I*** focus on framework for implementing data analytics using cloud and approach ***J*** uses RAMI 4.0 as the design guide, however they do not consider the wider aspect of advanced capabilities such as big data analytics, predictive model, etc., for managing predictive maintenance. Besides, these approaches including ***C, D, E, F, G*** in Table 5.1 still fail to address the complex and different systems i.e., CPS, robots, smart devices, collaborative manufacturing related processes such as design, maintenance, etc., that operate Industry 4.0 industries. Thus, this results in low applicability and subsequently low effectiveness for Industry 4.0. On other hand, we demonstrate PMMI 4.0 implemented in real-world industrial case (i.e., Section 5.4) utilizing different components of FIWARE in complying with Industry 4.0 standards. Since the PMMI 4.0 is designed to support modularity and interoperability, supporting dynamic needs, advanced capabilities such as big data analytics, predictive model, maintenance analysis, and requirements i.e., standards, etc., of Industry 4.0 systems, other industries cases can adopt our solution, particularly in dealing with dynamic needs and requirements of Industry 4.0 predictive maintenance systems.

5.5 Chapter Summary

In this chapter, we looked at the characteristics of industry 4.0, i.e. interoperability, modularity, Advanced capability and collaboration, the Predictive Maintenance model and architecture are designed and reviewed by using the characteristics of Industry 4.0.

- Section 5.3 proposed a flexible architecture model for Industry 4.0 Predictive Maintenance based upon the challenges (See Section 2.2.5), relevant requirements (See Section 2.5), and the key concepts of Industry 4.0 predictive maintenance (See Section 5.1.1). Three different components i.e., data acquisition, data process and prediction and maintenance decision support are the basis of our model.

  To support the aspect of flexibility or modular architecture platform for operating Industry 4.0 predictive maintenance systems, particularly in dealing with complex and dynamic nature and requirements, the proposed PMMI 4.0 is designed based on the flexibility which enables to easily integrate different processes/components based on different business needs.

  RAMI 4.0 architecture layers are used for simplifying the complex process and components involved in Industry 4.0 predictive maintenance. FIWARE framework have used for greater interoperability and integration (i.e. integrate with different software or components such as big data analytics, etc.), supporting dynamic needs and requirements of Industry 4.0 systems.

- Section 5.4 presented PMMI 4.0 implementation environment for the Flexible Manufacturing case. It demonstrated the end to end process and instantiation of PMMI 4.0 using different components, processes required for the capability of predictive maintenance in the industrial case.

- Section 5.4.2 provided the results of the evaluation and analysis that showed that PMMI 4.0 worked well with the industrial case of the FIRST project, in achieving modular platform with high interoperability, and advanced capabilities such as Big Data Analytics (Cosmos GE) component required for maintenance.

  In this context, the embedded predictive maintenance services such as predictive RUL models or scheduling can easily be adapted to different needs or new predictive models or maintenance services can be integrated into the existing modules or processes. The published journal/papers present the verification of PMMI 4.0 in the FIRST industrial manufacturing environment. It is noted that the implementation of FIWARE is generally based on an event-driven approach, and potential challenges such as increased complexity, security risks should be recognized and managed appropriately.

  It is noted that the implementation of FIWARE is generally based on an event-driven approach, and potential challenges such as increased complexity, security risks should be recognized and managed appropriately.

Overall, the evaluation and comparison in Section 5.4.2 and Section 5.4.3 demonstrates the applicability and verification of our proposed PMMI 4.0 approach in providing a flexible Industry 4.0 predictive maintenance.

The contributions including journal/paper publications of this chapter includes:

- A detailed Predictive Maintenance Process and Predictive Maintenance Model for Industry 4.0
- A flexible Predictive Maintenance Model for Industry (PMMI) 4.0 Architecture based on RAMI 4.0 and FIWARE
- Implement modules in FIWARE for PMMI 4.0 architecture model
- Design a new Industry 4.0 predictive maintenance platform for FIRST manufacturing case, applying PMMI 4.0 architecture
- Sang et al. 2020. Predictive Maintenance in Industry 4.0. In: Proceedings of the 10th International Conference on Information Systems and Technologies (Sang, Xu, de Vrieze and Bai, 2020*a*)
- Sang et al. 2020. Towards Predictive Maintenance for Flexible Manufacturing Using FIWARE. CAiSE 2020. Lecture Notes in Business Information Processing, vol 382. Springer (Sang, Xu, de Vrieze and Bai, 2020*b*)

- Sang et al. 2017. Simplifying Big Data Analytics Systems with a Reference Architecture. IFIP Advances in Information and Communication Technology (Sang et al., 2017)

- Sang et al. 2016. A reference architecture for big data systems. 10th International Conference on Software, Knowledge, Information Management & Applications (Sang et al., 2016*a*)

Chapter 6

Predictive Model for Maintenance

In this chapter, we discuss the utilization of the proposed predictive model of *PMMI 4.0* in Chapter 5 for predictive maintenance RUL, which is part of the Maintenance Analysis in Maintenance Decision Support of *PMMI 4.0* in Chapter 5. Factory business data such as machine sensor operation and condition data are accessed and processed using the proposed data model in Figure 5.2, *Data Model for Predictive Maintenance for Industry 4.0* along related predictive maintenance databases in Chapter 5. This chapter contains the published Paper 2[1] and Journal 1[2].

Industry 4.0 enables the collaborative industries in achieving high levels of flexibility and productivity (Thoben et al., 2017). In the context of Industry 4.0 manufacturing, different enterprises can move related business processes beyond its boundary including machines/devices/processes assisted by advanced technologies such as the internet of things, cyber physical systems, robots, etc. In this context, industrial systems are complex due, in part, to collaborative growing size, and to the integration of new technologies. In other words, there exist several complexities such as the complexity of machine equipment systems. With aging, these systems are subjected to failures, and maintenance activities are hard and expensive (Sang et al., 2021*a*). Moreover, the demands of high productivity, profit growth, operational availability, and safety, new innovative tools and methods are required (Sang et al., 2021*b*; Thoben et al., 2017). Thus, effective maintenance management becomes an important aspect for Industry 4.0 manufacturing organization. Recently, advanced method such as deep learning is widely explored for supporting predictive maintenance since deep

[1] Sang et al. 2020. Towards Predictive Maintenance for Flexible Manufacturing Using FIWARE. CAiSE 2020, Advanced Information Systems Engineering Workshops. Lecture Notes in Business Information Processing, vol 382. Springer (Sang, Xu, de Vrieze and Bai, 2020*b*)

[2] Sang et al. 2021. A Predictive Maintenance Model for Flexible Manufacturing in the Context of Industry 4.0. Frontiers Journal. doi: 10.3389/fdata.2021.663466 (Sang et al., 2021*a*)

learning can better handle big data including sensor data with the support of computing capability such as cloud, GPU, etc. (Goodfellow et al., 2016; Sang et al., 2017, 2021*a*).

In the context of predictive model, *remaining useful life (RUL)* is mostly suitable for predictive maintenance as it is being recognized simply by being able to accurately estimate the end of life of a machine component (Si et al., 2011; Tobon-Mejia et al., 2012). In this context, maintenance based on RUL predictions can facilitates better optimizations such as in time acquiring of resources e.g. spare parts, engineer, etc., ultimately effective maintenance scheduling. Particularly, cases with complex systems i.e. multiple machines components, are maintained, and associated costs are high, the accuracy i.e. high and medium may contribute to significant savings. Based on the predictive RUL and its corresponding horizon, performance indicators or parameters can be determined for predicting the failure time (Sang et al., 2021*a*).

In the context of Industry 4.0, there are collaboration of complex systems as well as resource dependency. For example, the machines/components in a product line of one manufacturing organization can be collaborated across multiple organizations (Sang et al., 2021*b*). Data of each machine/component, condition, etc. need to be captured for maintenance. In the case of conventional manufacturing, such resource dependency may not be important since the manufacturing does not need coordination or data across organizations and that it may own its capability. For Industry 4.0 predictive maintenance including predictive models, these dependencies such as resource must be considered (Sang et al., 2021*b*).

Predictive maintenance is based on data-driven methods and maintenance activity is scheduled in advance and acted before a failure event occurs (Mobley, 2002). A data-driven approach uses big data (operation, failure, etc.) collected from sensors, high computation and advanced machine learning (Mobley, 2002; Sang, Xu, de Vrieze, Bai and Pan, 2020). Thus, it offers advanced analytics and a cost-effective option, compared with traditional approaches such as model-based or experience-based methods which are based on physical failure models or experience, and hence are highly complex, difficult to build and maintain (Mobley, 2002). Moreover, both traditional maintenance approaches (reactive, preventive) face many challenges such as Industry 4.0, complexity of collaboration, big data, and computation (Mobley, 2002; Sang, Xu, de Vrieze, Bai and Pan, 2020).

In the context of building predictive models, RUL, tool wear detection such as worn, failure, degradation, are to be trained and evaluated. The models then can be deployed for prediction/detection of failure or degradation. Predictive models for maintenance along with related factory and maintenance information provide a basis for determining predictive maintenance activities. To develop a predictive model, various data such as operation and condition of machine/equipment tools, failure, etc. must be efficiently handled. In this aspect, various data such as manufacturing machine/equipment operational data collected via sensor are used. This sensor data is normally time series. Using this data, models are built to capture time sequence information for predictive models. Generally, traditional methods such as sliding window, sequence learning Hidden Markov Model and Recurrent Neural Network are used (Hashemian and Bean, 2011; Si et al., 2011; Tobon-Mejia et al., 2011). However, these approaches suffer from different challenges such as computational complexity, storage for modelling time sequence data. Thus, new approach for developing predictive models must be explored for Industry 4.0 focused industries to manage the various sensor data collected from the machine equipment tools.

In this work, a *Predictive Maintenance RUL Model* based on data-driven state of the art for supporting multiple machines components in Industry 4.0 manufacturing organization is proposed. The contributions include:

- Supporting predicting the RUL from short observation sequences since the initial condition of physical systems is usually unknown due to manufacturing deficiencies, replacements of parts of the system, and undesired maintenance. Hence, the network is designed to anticipate such requirements e.g., time window of RUL estimation.

- Supporting multiple machine component for complex high data feature of sensor operation data collected from factory operation and long-term learning by combining different neural network layers.

- A hybrid approach utilizing state of the art data-driven deep neural network approach which handles high sequence sensor data of multiple machine components and predict RUL estimation for maintenance.

- A modular approach supporting the model in dealing with multiple machine components, and the dynamic needs of Industry 4.0.

The general concept of data-driven predictive RUL model for maintenance is first discussed in Section 6.1. The problem formulation with related concepts is described in Section 6.2. The proposed Modular Predictive Maintenance Model using Hybrid Deep Learning Approach *(MPMMHDLA)* for predictive maintenance RUL is explained in Section 6.3, and the corresponding experiment, evaluation and comparison results are presented in Section 6.4. A summary of the chapter and the contributions are provided in Section 6.5.

6.1 Data-driven Predictive Maintenance RUL Model

Predictive maintenance is based on data-driven methods and maintenance activity is scheduled in advance and acted before a failure event occurs. Using data such as operation, condition, or time series (sequential) data, predictive models are built to capture information patterns which then can be utilized for predictive maintenance dealing with maintenance activities (Mobley, 2002).

Prognostics and health management (PHM) assists in reducing maintenance costs in industrial maintenance management. Due to its capability of determining the maintenance time, RUL prognostics is an essential function of PHM that has also attracted the interest of the research community (Mobley, 2002).

Different approaches such as model-based, data-driven, can be used for RUL prognostics (Sang, Xu, de Vrieze, Bai and Pan, 2020; Tobon-Mejia et al., 2012). Model-based methods are based on the degradation models of the physical structure and thus are unable to deal with complex structure of machines (Tobon-Mejia et al., 2012). On the other hand, various data such as sensor measurement, operational are used for data-driven approaches and hence, the knowledge of the physical structure and degradation are not required. Alternatively, a combination of both model-based and data-driven, called data fusion may be applied. This approach still is required dealing with the physical structure which tends to be undiscovered intricacy.

Prediction methods of sequence learning or time series are the focus of data-driven research for RUL prognostics due to the intrinsic nature of sequence or time series (Zheng et al., 2017). Several approaches based on analysis of sensor time series data and discovering relevant patterns associated with the prognostics task, have been proposed for RUL prognostic models (Srivastava and Mondal, 2016). These approaches offer an effective solution to the manufacturers (Mobley, 2002; Tobon-Mejia et al., 2012). The utilized techniques for prediction models include auto-regressive integrated moving average-based (ARIMA) models (Wu et al., 2007), hidden Markov models (HMM) (Baruah and Chinnam *, 2005), support vector regression (SVR) models (Benkedjouh et al., 2013), artificial neural networks (ANNs) (Arnaiz-González et al., 2016), random forest (RF) regression (Wu et al., 2017) and so on. These approaches deal with traditional dataset i.e., structured, and thus face challenges regarding big data i.e., complex, high frequency, and unstructured including streaming (Gers et al., 2000; Sang et al., 2017; Sang, Xu, de Vrieze and Bai, 2020*a*; Si et al., 2011).

Deep learning has become one emerging research area in prognostics due to the rapid and increasing development of modern computations such as cloud, resources for computational efficiency that enhance the capability in complex system models (Goodfellow et al., 2016). There are different deep learning architectures: *auto-encoder, deep belief network (DBN),* *convolutional neural network (CNN), recurrent neural network (RNN) and long short-term memory (LSTM)* (Zhao et al., 2019). *Auto-encoder* is capable of learning efficient representations of input data in an unsupervised manner and is often used in data or network pre-training (Goodfellow et al., 2016) whereas *DBN* is capable of revealing deep data patterns and it utilizes a feed-forward neural network with multiple hidden layers. *DBN* consists of a stack of restricted Boltzmann machine and a supervised perceptron (Hinton et al., 2006). As for *CNN*, it derives from the inspiration of human brain cortex. It is capable of extracting abstract features by sequential operations of convolution and pooling (LeCun and Bengio, 1995). In the case of *RNN*, it is capable of retaining the recent memories of input patterns. Its variant, *LSTM* network further addresses the problem of capturing the long-term memory (Gers et al., 2000; Goodfellow et al., 2016; Hochreiter and Schmidhuber, 1997). *LSTM* resolves the long-term time dependency problems by controlling information flow using the input gate, forget gate and output gate (Goodfellow et al., 2016; Hochreiter and Schmidhuber, 1997).

In the context of developing prediction models for maintenance, models such as RUL, tool wear detection aspects such as wear, failure and degradation are trained and evaluated before deployment (Hashemian and Bean, 2011; Sang, Xu, de Vrieze and Bai, 2020*b*). In this aspect, various data such as manufacturing machine/equipment operational data collected via sensor are used. This sensor data is normally time series. Using this data, models are built to capture time sequence information for predictive models. Methods such as sliding window, sequence learning Hidden Markov Model (HMM) and Recurrent Neural Network (RNN) are largely used (Gers et al., 2000; Si et al., 2011). HMM approach was used in sequence learning, however it suffers from computational complexity and storage. In the case of auto-encoder method, for bearing degradation model, an auto-encoder detecting starting point of the degradation and a stacked denoising auto-encoder (SDA) for fault detection are used for prognostic (Hasani et al., 2017; Lu et al., 2017). For DBN approach, a DBN-based method for material removal rate prediction in polishing as well as a new regularization term for predicting machine RUL are utilized (Liao et al., 2016; Wang, Gao and Yan, 2017). Regarding CNN, a method for fault inference in semiconductor manufacturing process as well as an approach for learning features from time-frequency scales directly for automatic fault related pattern recognition (Lee and Pan, 2017; Wang, Ananya, Yan and Gao, 2017). For LSTM, it has been applied for predicting tool wear (Zhao et al., 2016), lithium-ion battery cell capacity (Zhang, Lim, Qin and Tan, 2017) and bearing health state (Chen et al., 2017).

At this stage, existing predictive maintenance approaches still fail to address the challenges such as complex multiple machine equipment tools with diverse sensor operation/data condition data, posed by Industry 4.0 focusing manufacturing organization. Based on these challenges as well as the key issues discussed in Section 2.3.3, Section 2.5, it is clear that there is an opportunity for an approach that considers multiple machine components involved in complex manufacturing. The approach should be based on data-driven method as traditional methods such as reactive and preventive cannot deal with the complexity and demands of Industry 4.0 (Mobley, 2002; Sang, Xu, de Vrieze, Bai and Pan, 2020; Tobon-Mejia et al., 2012). Essentially, a hybrid approach is needed, utilizing state of the art data-driven deep neural network approach which handles high sequence sensor data of multiple machine components and predict RUL estimation for maintenance that can be managed in a modular manner.

6.2 Problem Formulation for Predictive Maintenance

6.2.1 Problem Formulation of Predictive Maintenance RUL

Predicting a potential failure of a machine/component is part of a predictive maintenance process. It is the stage of predictive maintenance for the estimation of remaining useful life (RUL), incorporating different needs and constraints. Predictive maintenance RUL involves building the predictive model using big data that are generated by the machines components of a complex system. It demands a detailed description of the predictive maintenance process including multiple machine components, complex high data feature of sensor operation data and advanced machine learnings. As it is clear, these predictive maintenance problems have a strong combinatorial nature and consequently a high complexity, particularly in the context of complex Industry 4.0 environment. As such, the predictive maintenance model should be flexible enough to support a predictive model, that can be adapted to dynamic needs of Industry 4.0.

A modular predictive maintenance model is based on a hybrid approach which utilizes data-driven (sensor operation, condition data) and state of the art deep neural network. A hybrid approach allows combining different neural network layers such as Convolutional, LSTM, for an optimal model based upon performance metrics such as RMSE, particularly in dealing with complex high data feature and long-term learning. Predicting the RUL from short observation sequences (i.e. the initial condition of physical systems is usually unknown), indicates that the predictive model depends on requirements such as time window of RUL estimation, target functions such as piece-wise linear.

To support predictive maintenance of a service, predictive models are stored in, and can be used from, a model repository. These predictive models (i.e., deep neural network models), can be parameterized to work with data from various machines or devices. To aid users in selecting appropriate models, the repository provides selection criteria for the models.

6.2.2 Dataset for Predictive Maintenance RUL Model

In the context of Industry 4.0, resource dependency such as machines/components in a product line from one manufacturing organization to collaborative multiple organizations. The factory related data of each machine/component, condition, etc. need to be captured. In the context of Industry 4.0 FIRST flexible manufacturing case in Section 3.1, the data collection (i.e. Section 5.2.1 in Chapter 5) in general is online activities. In this context, the operation data of the machine equipment tools are first to be acquisitioned within a product line of flexible manufacturing; online data collection allows data to be received synchronously from the product line. And the real-time data can better reflect the machines' conditions. In a flexible manufacturing setting, various data such as event, operation, and condition data, are being gathered during operation. For event data, it refers to data about the assets i.e. machine equipment tools with respect to the breakdown or failure event of the asset as well as the specific maintenance that was performed. In the case of operation data, data is collected from a certain process whereas the condition data may involve collecting data about the general condition i.e. health and measurements of the asset. Using different sensors, different signal data such as vibrations, temperature, pressure, are collected as part of the data acquisition i.e. event, condition (Sang, Xu, de Vrieze and Bai, 2020*b*). Using operational and condition data collected from the manufacturing machine/components, predictive maintenance models are built to capture time sequence information.

Essentially, the dataset required for predictive maintenance can be expressed as: dataset of sensor/time series $d\left[O_n, C_n, Mb_n\right]$ of multiple machine components $m[n]$. d denotes the sample dataset, O represents the sensor time series operation data features such as cycle, setting, pressure, voltage, etc., of the multiple machine equipment from the factory operation whereas the machine base Mb represents the machine data features such as the normal configuration, model, etc., as well as the condition C represents the health status features such as worn, failed, good, etc.

6.2.3 Performance Measurement of Predictive Maintenance RUL Model

In the context of RUL regression problem, *Root Mean Square Error (RMSE)* is widely used for performance analysis (Al-Dulaimi et al., 2019; Sateesh Babu et al., 2016; Si et al., 2011; Zheng et al., 2017). In this work, similar approach, *RMSE* is thus utilized for the performance evaluation of the RUL prediction. In this instance, the error in predicting the RUL of the n machine/component is given by

$$E_n = RUL_{Predicted} - RUL_{Actual}. \tag{1}$$

En can be both positive and negative. And the outcome of E being positive will be undesired and that will indicate that the machine/component will fail before the estimated time. Therefore, a scoring function that penalizes positive *En* value is used, and is given by

$$S = \begin{cases} \sum_{i=1}^{N} \left(e^{-\frac{E_i}{13}} \right) & E_i < 0 \\ \sum_{i=1}^{N} \left(e^{-\frac{E_i}{10}} \right) & E_i \geq 0 \end{cases} \tag{6.1}$$

To this end, the sensitivity of the outliers still needs to be managed. In this instance, one single outlier can still impact the score value as there is no error normalization and it follows an exponential curve. Therefore, *RMSE* is applied and given by

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} d_i^2}. \tag{6.2}$$

6.2.4 RUL Target Function for Predictive Maintenance RUL Estimation

In the industrial applications within complex systems, it is not possible to evaluate the exact condition and estimate the RUL of the system at each time step without an accurate physics-based model (Mobley, 2002). This means that the desired output of the input data is not easy to determine for a remaining useful life prediction problem. On the other hand, over time, the performance of machine equipment tools along with the corresponding deteriorations may change sensor measurements, which are an important aspect for prognostics techniques (Mobley, 2002; Sateesh Babu et al., 2016; Si et al., 2011; Zheng et al., 2017). In the context of regression problem for RUL estimation, a piecewise function is effective in existing approaches (Sateesh Babu et al., 2016; Si et al., 2011; Zheng et al., 2017). Based upon the adoption of the data-driven approach and availability of dataset, a piecewise function for predictive RUl estimation is adopted in this work.

An example of data variation can be seen in Figure 6.1. At the preliminary state, RUL estimation is not possible to predict since the machine equipment tool has not been operated and hence no operation or condition data is available. In this aspect, it is presumed that RUL is a constant *Eth* until it reaches the critical point of *Eth* in the first stage. In the next

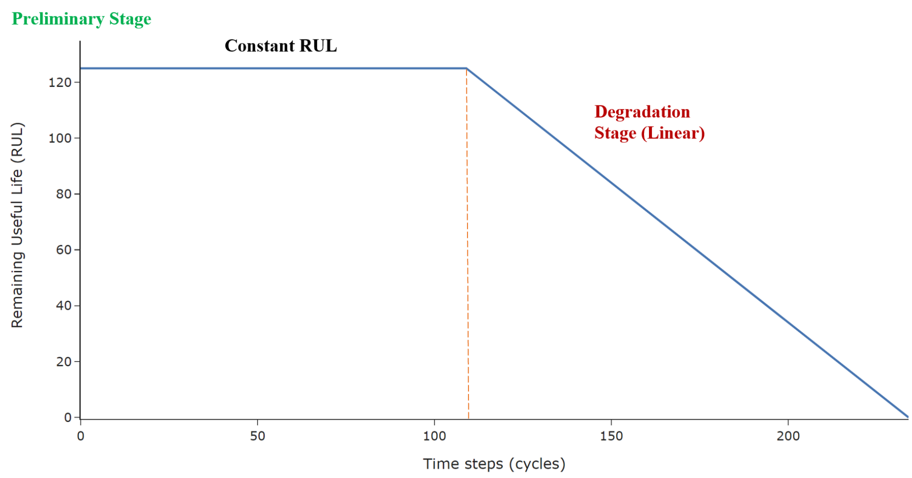


Fig. 6.1 An Illustration of Piece-wise linear target function for predictive RUL estimation (Tobon-Mejia et al., 2012)

stage, RUL can then be represented by a linear function. Thus, the entire RUL curve can be described as a piece-wise linear function, as shown in Figure 6.1, either to rise or fall over time in a sequence. In the context of manufacturing, the entire operation or next failure stage of the machine equipment tool can be described by: the normal operation or performance stage (i.e., the constant RUL in Figure 6.1) which illustrates a relatively flat trend and the degradation stage (i.e., linear degradation in Figure 6.1) which illustrates an approximately exponential dropping trend.

To avoid over estimation, the target function is set for an upper bound of the maximum RUL. Generally, the degradation of the system starts after a certain degree of usage, and hence, it is considered that this model is more suitable, compared to the linear degradation model (Peel, 2008). Using the target function and the train trajectory T_n, the RUL values for machine/component $n \in 1, ..., N$ can be generated for a given $P_n \in \mathbb{P}^{T_n \times 1}$ where $P_t n \in P$ denotes the RUL value of machine/component n at the t-th time step. The RUL values of all N training machine/component can be represented using the set $P = \{P_n^t | n = 1, ..., N; t = 1, ..., T_n\}$. These RUL values act as the labels for the training in the proposed model architecture which is discussed in Chapter 7.

6.3 Predictive Maintenance Model for RUL

Industry 4.0 focusing manufacturing operates with many different systems, machine equipment tools including CPS, CNC, robot, processes, etc. To employ predictive maintenance, the data generated by these different factory systems must be processed as discussed in

Section 5.2 in chapter 5. However, traditional data processing and tools and existing methods such as HMM, RNN are not efficient for dealing with complex data such as factory sensor data as well as dealing with dynamic needs of Industry 4.0 (i.e. Section 6.1, Section 2.3.3, Section 5.2.3.1) (Brewka, 1996; Mobley, 2002; Sang et al., 2017, 2021*a*; Sang, Xu, de Vrieze, Bai and Pan, 2020; Si et al., 2011). To respond to this as well as the requirements identified in Section 2.5 (i.e. Section 2.5.3, Section 2.5.6, Section 2.5.5), we thus propose a method, Modular Predictive Maintenance Model using Hybrid Deep Learning Approach *(MPMMHDLA)* as presented in Figure 6.2.

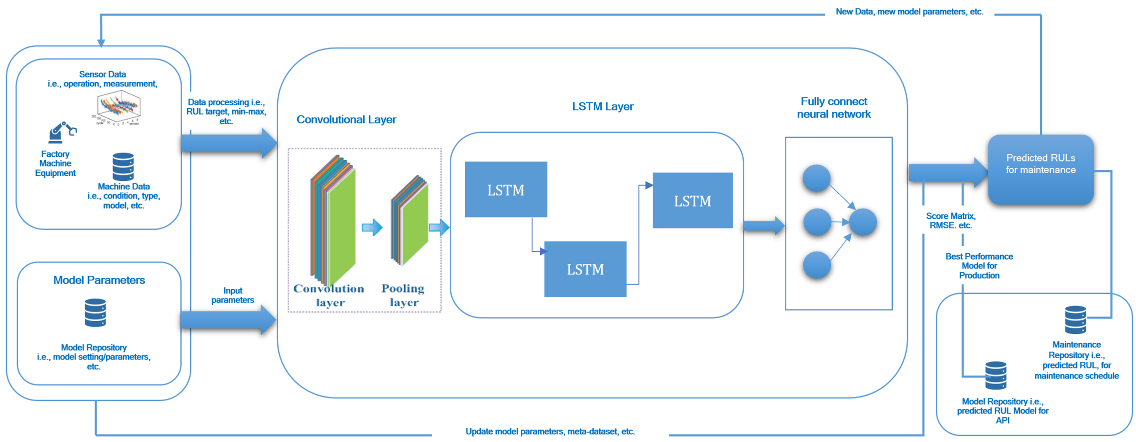


Fig. 6.2 Modular predictive maintenance model using hybrid deep learning approach (MPMMHDLA)

The proposed model consists of data pre-processing, model parameters input, and a deep neural network regression model for RUL estimation as well as accessing related maintenance and model repository in a modular manner. As shown in Figure 6.2, both training and testing data of the sensor operation and condition data of the machines/components are processed and normalized as sequence features before processing into the model. Model parameters such as number of convolutional, LSTM layer, etc., are provided as input. The model is then composed of the inputs i.e., stacked convolution layers and LSTM layers, which are connected with each other using fully connected layers for producing RUL values in the proposed model architecture. Based on model performance such as RMSE score, best performance model is used for production and that corresponding RUL values of the machines/components are available via the API as shown in Figure 6.2 (i.e., Figure 5.4 of *PMMI 4.0* in Chapter 5).

Unlike existing methods such as Zheng et al. (2017), Sateesh Babu et al. (2016), we consider modularity, one important aspect of Industry 4.0 as discussed in Section 5.1, Section 6.1, Section 2.3.3, Section 5.2.3.1. To support modularity particularly in the context of dynamic and complex Industry 4.0 environment, new optimized model based on new sensor data, different input parameters i.e., number of different layers, etc., can be developed and subsequently the optimized model can be deployed and the meta model data such as parameters, settings, dataset, etc. can be stored in the model repository for input parameters or configurations that can be re-used. This process is facilitated by the *Predictive Model Process* which is described in Figure 6.3, in the next Section 6.3.1.

In the context of Industry 4.0 manufacturing, multiple machines/components operate for business factory operation. In our approach, the data i.e., sensor collected from the various machine equipment tools including machine data such as condition, type, etc., as well as the model parameters i.e., convolutional, LSTM layers, etc., are taken as inputs. These input data are processed into features that fed into the convolutional layer, given convolutional layer input is provided. As inspired by the capability of convolutional neural network (Sateesh Babu et al., 2016), the convolutional layer is applied for identifying the various distinctive patterns of sensor measurement data and extract high-level spatial features. In most cases a higher dimensional data framework is processed by placing a filter over the data. This filter is known as a kernel, which can highlight and specify certain features in the data.

The data features are obtained from the pre-processing. In this instance, each of the data *nk* kernels are applied of size *[k1, k2]* with a stride of *[s1,s2]*, and the data size is reduced to *m2*. The output of the convolution derives from a pooling layer operation, where the max pooling applies a kernel like operation, except the largest value in this filter is the new value. Then, the outputs of the convolutional layer are mapped into LSTM layers, given LSTM layer input(s) is provided. LSTM processes the sequence data features with long-term memory, being capable of the data information backward as well as forward. In this aspect, the data information is handled by three gates i.e., input, output and forget, modulating the flow of information in the LSTM cell. The input gate controls of the information being carried to the memory cell based on previous output and current sequence data, the forget gate controls of the memory cell being updated, and the output gate controls of the information being passed to next time-step. In this way, our approach is designed to handle potential complex sensor operation and condition data from machines/components of Industry 4.0 manufacturing, compared with the existing methods in Section 6.4.2.4.

In general, the convolutional layer and the long-term temporary memory of LSTM can be expanded, as part of the modularity proposed in our approach. Particularly, if there are high-frequency data/sensor measurements or various sensors involved, it may be ideal to add a convolutional layer before the LSTM layer (Goodfellow et al., 2016). In this aspect, pooling layers are implemented with convolution layers, to reduce computation time and to gradually build up further spatial and configural invariance. And LSTM is utilized to resolve long-term temporary dependency features. The fully connected neural network is utilized for mapping, and the Deep Convolutional Long Short-term Memory Network will learn an optimized model to predict machine/component RUL as shown in Figure 6.2. The goal of the proposed method is to process the sensor operation and condition data after feature extracting and nonlinear regression by multilayer networks, then the machine machine/component RUL is obtained. To assist the overall *MPMMHDLA* process, predictive model process for our model is presented in the next Section.

6.3.1 Predictive Model Process for MPMMHDLA

For developing predictive model for *MPMMHDLA*, the process is adapted from Chapman et al. (2000) (i.e. Section 4.3.3) and Sang, Xu, de Vrieze and Bai (2020*a*), which is part of the research method as described in Figure 4.9 in Chapter 4. The predictive model process is presented in Figure 6.3.

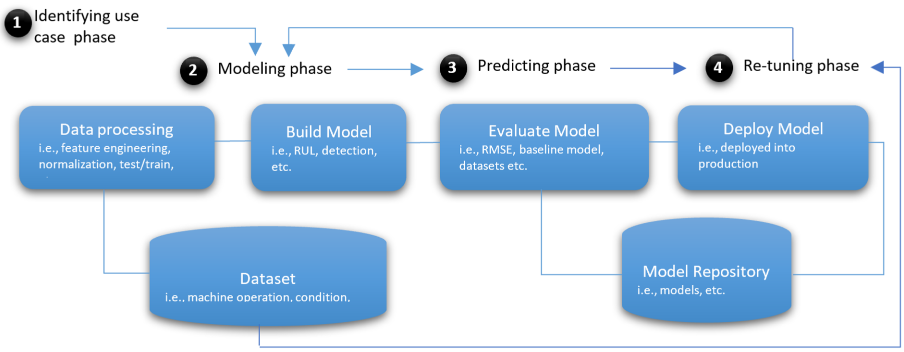


Fig. 6.3 Predictive modelling process for MPMMHDLA (Chapman et al., 2000; Sang, Xu, de Vrieze and Bai, 2020*a*)

The *Predictive Model Process* presented in Figure 6.3 includes identifying the business use case, data acquisition, data pre-processing, development of detection or prediction model and deployment and integration of the developed model. In the context of Industry 4.0, specifically FIRST industrial case (i.e. Section 3.1), multiple different machines/components involve in the factory production chain, hence further considerations such as multiple resources, machines, data fusion and processing, etc., are recognized.

The understanding of the architecture design, the utilization of underlying processes, technologies and services of big data systems are realized for designing effective capabilities of predictive maintenance (Sang et al., 2017). The approach for predicting maintenance offers the fundamental understanding of the general approach for developing the function of predictive maintenance analytics including predictive model for maintenance.

The *Predictive Model Process* in Figure 6.3 also assists the modular aspect of the proposed predictive model, *MPMMHDLA* in Figure 6.3, facilitating the overall process of the model which is discussed in Section 6.3 and Section 6.3.5.

6.3.2 Data Processing for MPMMHDLA

In the context of Industry 4.0, various systems, and machine equipment tools such as CPS, robots, CNCs, etc., operate during factory operation. Different sensor enabled devices i.e., IoT adapters, etc., are utilized for collecting the voluminous and diverse data. Thus, the operation sensor data can be complex and multidimensional. Generally, features with low variance are convergent, i.e., features that are not obviously distinguishable, and they are ineffective against prognostics performance (Mobley, 2002; Tobon-Mejia et al., 2012). Thus, features with a dataset variance lower than threshold e.g., inconsistent/incomplete sequence data for specific time window, noisy data, etc., will be removed. It is formulated as:

$$f = x : variance \sum_{m=1} (x_m, x) \geq t \tag{6.3}$$

where f is the input feature, m is the sample size and x represent the mean of the feature.

Furthermore, the scales of the sensor data value may be diverse. Data normalization i.e., the process with respect to each sensor before utilizing data, is applied to accelerate the convergence rate (Patro and Sahu, 2015). In this work, two main data normalization methods, *z-score normalization* at *Equation 6.4*, and *min–max normalization* at *Equation 6.5* are utilized (Patro and Sahu, 2015; Zheng et al., 2017). For the normal distribution of the sensor data, *z-score* method is specifically applied. And for scaling i.e., within the range of *[0, 1]* of the sensor data, *min–max* normalization method is applied for our model MPMMHDLA.

$$\mathbf{x}_i' = \frac{\mathbf{x}_i - \mu_i}{\sigma_i} \tag{6.4}$$

$$\mathbf{x}_i' = \frac{\mathbf{x}_i - \min\ \mathbf{x}_i}{\max\ \mathbf{x}_i - \min\ \mathbf{x}_i} \tag{6.5}$$

where *max, min* are the maximum, minimum and σ_i is standard deviation with respect to each sensor μ_i respectively, and $\mathbf{x}_i'$ is the normalized sensor data.

In the context of Industry 4.0 manufacturing operation, multi-variate sequence or time series data may be produced by the various sensor enabled machine equipment tools (Sang, Xu, de Vrieze and Bai, 2020*a*). For regression problems such as RUL estimation, the temporal sequence data compared with the multi-variate data point sampled at a single time step may produce more advantageous information (Mobley, 2002). In this aspect, time sequence processing has a significant potential for better prediction performance (Gers et al., 2000; Hashemian and Bean, 2011; Tobon-Mejia et al., 2012).

In this work, a time window is thus applied for the sensor data feature of the machines/components that may possess multi-variate temporal information, and subsequently leads to potential performance gain, compared with existing approaches in Section 6.1 that do not consider the aspect of the potential impact of the multi-variate temporal sensor data which may be collected from Industry 4.0 focusing manufacturing operation and processing. In practice, it can be described as $N_t w$ denote the size of the time window, and all sensor data within the time window are collected at each time step, to form a vector of a high-dimensional feature that can be used as the inputs for the network.

6.3.3 Convolutional Layer for MPMMHDLA

Since Industry 4.0 focusing manufacturing operates with complex systems, machine equipment tools, etc. These different systems/machines generate many different factory operation data such as sensor data, which is of high frequency and dimensional that is challenging for traditional methods (Bai et al., 2018; Gers et al., 2000; Sang et al., 2021*a*; Zheng et al., 2017). To better support this, convolutional layer is applied to our model, *MPMMHDLA*, since convolutional neural network is capable of learning feature patterns from high dimensional data (Bai et al., 2018).

Generally, a convolutional layer may be composed of 1D convolution and 1D-max-pooling (Goodfellow et al., 2016). Regarding the convolution, let *d(C-1)* and *d(C)* be the input and the output of the C_{th} layer, respectively. Input to the C_{th} layer is the output of the $(C-1)_{th}$ layer. As several feature maps are used for a layer, we denote the *j-th* feature map of layer C as *d(C)j*, and this can be computed by

$$d_j^{(l)} = f\left(\sum_i d_i^{(l-1)} * \vec{w}_{i,j}^{(l)} + b_j^{(l)}\right), \tag{5}$$

where * denotes the convolution operator, $\vec{w}_{i,j}^{(l)}$, and $d_j^{(l)}$ represent the 1-D weight kernel and the bias of the j_{th} feature map of the l_{th} layer, respectively, and f is a nonlinear activation function. A rectified linear unit activation (ReLu) in this case is applied (Goodfellow et al., 2016).

For assisting in decreasing the spatial size of the feature representations, the pooling/sub-sampling is applied (Goodfellow et al., 2016). In this way, computational efficiency is better achieved and the degree of parameters that controls over-fitting of neurones is minimized. Max-pooling is the most recognized operation of pooling/sub-sampling in convolutional neural network and it can operate independently from the convolutional operation (Goodfellow et al., 2016). The 1D-max-pooling is given by

$$d_{ji}^{(l)} = \max\left(d_{j_{i_{nbh}}}^{(l)}\right), \tag{6}$$

where $d_{ji}^{(l)}$ denotes the i-th element of feature map $d_j^{(l)}$, $d_{j_{i_n dh}}^{(l)}$ denotes the set of values in the 1D-neighbourhood of *d(l)ji*. The neighbourhood size is defined by the 1D-pooling size.

6.3.4 Long Short-Term Memory (LSTM) Layer for MPMMHDLA

Due to its capability of processing sequential data and long-term memory, compared with traditional methods such as SVM, HMM, RNN (Bai et al., 2018; Gers et al., 2000; Goodfellow et al., 2016; Hochreiter and Schmidhuber, 1997; Sang et al., 2021*a*; Tobon-Mejia et al., 2012; Zheng et al., 2017), LSTM is adopted for MPMMHDLA. This enables MPMMHDLA better supporting of factory sensor/time-series data such as machine tools operation, condition.

For a given input data feature sequence $X_n = \left(X_n^1, ..., X_n^T\right)$, a recurrent neural network (RNN) generates an output of $Y_n = \left(Y_n^1, ..., Y_n^T\right)$ using the hidden vector sequence of *ht = h1, ..., hT*. This is achieved by iterating the following equation from *t = 1 to t = T*:

$$h^t = f\left(W_{xh}X_n^t + W_{hh}h^{t-1} + b_h\right), \tag{7}$$

$$Y_n^t = W_{hy}h^t + b_y, \tag{8}$$

where *Wxh, Whh and Why* denote the transformation matrices of the input and hidden vector, and *bh*, by are the bias vectors. The RNN generates the output of the temporal variations, however it suffers from memory connectivity. Memory gates are thus applied for the RNN cells, known as long short-term memory networks (LSTM) (Hochreiter and Schmidhuber, 1997). The computation of *ht* for the LSTM networks follows from:

$$i^t = \sigma\left(W_{ix}X_n^t + W_{ih}h^{t-1} + W_{ic}c^{t-1} + b_i\right), \tag{9}$$

$$f^t = \sigma\left(W_{fx}X_n^t + W_{fh}h^{t-1} + W_{fc}c^{t-1} + b_f\right), \tag{10}$$

$$c^t = f^t c^{t-1} + i^t \tanh\left(W_{cx}X_n^t + W_{ch}h^{t-1} + b_c\right), \tag{11}$$

$$o^t = \sigma\left(W_{ox}X_n^t + W_{oh}h^{t-1} + W_{oc}c^t + b_o\right), \tag{12}$$

$$h^t = o^t \tanh\left(c^t\right), \tag{13}$$

where *o* denotes the logistic sigmoid function, and *i, f o and c* represent the input gate, forget gate, output gate and cell activation vectors, respectively. The transformation weights *Wix, Wih, Wic, Wfx, Wfh, Wfc, Wcx, Wch, Wox, Woh, Woc* and bias values *bi, bf, bc, bo* are computed during the training process. The input gate *it*, output gate *ot*, and forget gate *ft* control the information flow within the LSTM network. Several gates are utilized in LSTM network which can keep selective memory compared to an RNN. The LSTM layer can be presented by an array of LSTM (Hochreiter and Schmidhuber, 1997).

6.3.5 MPMMHDLA for Predictive Maintenance RUL Model

In the context of Industry 4.0, multi-variance sensor sequence/time series data are generated by the various machine equipment tools, operating for different business needs. Existing approaches as discussed in Section 6.1 suffers different challenges such as computation, memory storage, etc. To overcome this, we propose a deep convolutional long short-term memory networks for predictive maintenance RUL model. MPMMHDLA is implemented by both convolutional and LSTM layers with a fully connect layer.

The proposed model architecture is designed based on a hybrid approach which composed of different neural network layers. In our approach, dealing with complex and diverse data such as sensor measurement and operation data from factor machine equipment tools, convolutional layer with pooling layer is utilized to reduce computation time as well as to gradually build up further spatial and configural invariance. To learn the sequence feature data, which is the output of the convolutional layers, LSTM layers are connected for long-term temporary dependency features. Both convolutional and LSTM layers are then implemented and mapped via a fully connected neural network to form a fully hybrid deep neural network. The hybrid deep neural network will then learn an optimized model to predict the RUL of the machine/component. In this way, the sensor operation and condition data of the machine/component after feature extracting are processed by an optimized hybrid networks and then the machine/component RUL is obtained.

In the case of dealing with training data problems such as overfitting, dropout technique is widely applied (Goodfellow et al., 2016). Overfitting is the effect that occurs when too many training iterations are performed (Goodfellow et al., 2016). This results in the model being only able to predict the training data. Other input data will result in inaccurate results. Therefore, the amount of training iterations (epochs) should be regulated, and the final should be based on a separate training set. Data processing is applied as previously discussed in Section 6.3.2.

In the context of deep neural network learning, dropout can be applied by controlling the flow of the activated neurons in the forward propagation over the training process by setting zero to the outputs of some of the hidden neurons. For better robustness of the network, dropout is however not included in the testing process, that indicates all the hidden neurons are involved during testing. Besides, dropout can be utilized for model ensemble within the network, assisting to improve the feature extraction capability of the network. In our approach, dropout is considered for reducing data overfitting. In this way, dropout method provides an easy and effective way to reduce the problem of data overfitting, subsequently the training data overfitting generally results in good network performance on the training dataset and poor performance on the testing dataset (Goodfellow et al., 2016).

In this study, the dropout technique is thus applied on the proposed hybrid network to prevent complex co-adaptations on the training data and avoid the extraction of the same features repeatedly (Goodfellow et al., 2016). In the proposed approach in Figure 6.2, a fully connected layer with dropout regularization is applied to connect the convolutional layer to the LSTM layers. As described in Section 6.3.2, data contains operating conditions and sensor operation measurements. These data represent the number of channels in the input, as well as the length of the sequence. Therefore, the input to the first convolutional layer can be represented as $Xtn \mid t = ti, ..., ti + sequence\ length$, where ti is the end time step of the previous input of the first convolutional layer. The LSTM layer size is configured empirically. The final fully connected hybrid network layers work as regression model to estimate the RUL values.

6.3.6 Applying PMMI 4.0 and MPMMHDLA for predictive maintenance RUL

In our *PMMI 4.0* i.e., Figure 5.4 in Chapter 5, using sensor data collected from machine equipment tools, predictive maintenance RUL, *MPMMHDLA* model is developed as described in Figure 6.2. At the predictive models in our *PMMI 4.0* architecture (i.e., Figure 5.4

in Chapter 5), the optimized models can be deployed and used via API for maintenance analysis and schedule plan at the maintenance decision support.

One important aspect of Industry 4.0 predictive maintenance is supporting flexible and modular feature which can assist in dealing with complex systems and business change/needs in a dynamic and modular manner. Besides, factory data such as machine operation, condition, etc., are diverse, high frequency as well as voluminous in increasing collection as well as availability. In our approach as previously described in Figure 6.2, we thus consider the aspect of modularity by supporting flexible and hybrid approach where new data i.e. sensor operation/condition data collected from the machine equipment tools or new model optimized i.e. training the model with required model parameters such as number of convolutional, LSTM layer, dropout rate, etc., can be developed and deployed. Using model repository described in Figure 6.2, optimized models including model configurations/parameters can be recognized. This can potentially facilitate different optimized models for different maintenance cases such as CPS, CNC, robots, etc., particularly for better handling complex systems of Industry 4.0 manufacturing such as the application cases (i.e., flexible manufacturing and virtual factory in Chapter 3).

In the case of handling data, using components such as FIWARE's big data analysis with related data adapters and processing, both online and offline (batch) processing can be supported on *PMMI 4.0* as shown in Figure 5.4 in Chapter 5. These data can be factory sensor operation/condition data, other factory related information systems such as MES, ERP, etc. The usage of these data including dataset, model configurations/parameters, performance metrics, etc., then can be recorded in the model repository depicted in Figure 6.2 for the corresponding trained model as well as the usage of the deployed model in operation for monitoring and optimization purpose. These data from the model repository can be utilized for developing more effective and optimized one when a new model is trained, enabling continuous enhancement in a dynamic and modular way.

From the user perspective, the predictive maintenance RUL model deployed can be available via the API for the maintenance engineer/user on *PMMI 4.0* as shown in Figure 5.4 in Chapter 5. Using the deployed model, upcoming predictive RUL values of the machines/components can be generated, and subsequently appropriate maintenance actions can be scheduled (i.e., detailed explanation is provided in Chapter 7). For model development, related information such as dataset, features, model configurations/parameters, performance metrics, etc., can be available at the maintenance decision support in *PMMI 4.0*. Based on the information, the maintenance engineer can also select specific models (i.e., based on deployed models such as *MPMMHDLA* or a particular optimized model such as LSTM or CNN for specific machine/component tools (i.e., based on better model performance, etc.) as part of the modular aspect that our approach supports. Using the dataset from the application case, we explored different models and their performance in our experiments in Section 6.4.2. And at this stage, the best performance model for the machines/components in Section 6.4.2.1 can be deployed and available for the maintenance engineer at the maintenance decision support of *PMMI 4.0*. Since our approach is designed in hybrid and modular manner, further dataset i.e., sensor data of robots, etc., will easily be acquired, processed, and utilized for *MPMMHDLA* model, similar procedures i.e., model configurations/parameters, etc., will be applied and the corresponding models including *MPMMHDLA*, and other models described in Section 6.4.2.2 will be evaluated and deployed accordingly.

At this stage, we only focus on predictive maintenance RUL model with available dataset from the FIRST industrial case. Besides, different predictive maintenance models such as failure detection e.g., classification approach for shorter window time or different optimization models for factory or machine operation, etc. based on business needs may also be developed, evaluated, and deployed on *PMMI 4.0*, following our approach *MPMMHDLA* depicted in Figure 6.2.

6.4 Experiment Study

In this section, we have performed extensive experiments for the evaluation of the proposed model in Figure 6.3 in Section 6.3. We analyse the model performance, the impact of the hybrid network layers, time window on the RUL estimation including performance comparison with different methods and related works. First, we describe the experiment setting including the FIRST manufacturing dataset as well as the different methods and related works which are used for performance comparison against our model in Section 6.4.1. In Section 6.4.2, we present and discuss the experiment results including RUL performance, comparison performance results.

6.4.1 Experiment Setting

6.4.1.1 FIRST Manufacturing Dataset

To demonstrate the effectiveness of the proposed solution, the data used must reflect or meet the nature and requirements of Industry 4.0 i.e., multiple machine components. In the described FIRST manufacturing case in Chapter 3, manufacturing dataset includes both operation and sensor time-series data which consists of different measurements including voltage, pressure, rotation, etc., collected from multiple machines/components in real time collected during factory operation.

Table 6.1 Overview of Manufacturing Dataset for Training Predictive Maintenance RUL Model

Feature	Data Type
Machine	int
Cycle	int
Machine Condition	int
Pressure	float
Voltage	float
Vibration	float
Rotation	float
Model	int

An overview of the dataset is also provided in Table 6.1. The data consists of voltage, rotation, pressure, and vibration measurements collected from different machines. The first feature represents the id of the machine/component and the second value represents the operational cycle. The machine condition feature represents the degradation state of the machine health. The pressure, voltage, vibration, and rotation describe the operational state of the machine in factory production. The model represents the model number of the machine component. The error represents the indication of failure error for the representative machine.

One training set and one test set is derived from processing the dataset. In the training dataset, there are sensor operation records of multiple machine/components collected under different operational conditions and fault modes including run-to-failure which is used for generating RUL value. At the start of each cycle for each machine/component, it is considered as healthy because different degrees of initial wear and manufacturing variation are mostly undistinguishable and unknown. Over time, factory operation progresses, and each machine/component begins to degrade until it reaches to the point of failure, i.e., the last data entry corresponds to the time cycle that the machine/component is regarded as unhealthy.

On the other hand, the sensor records in the testing datasets terminate at some time before the failure, and the goal of this task is to estimate the remaining useful life of each machine/component in the test dataset. For verification, the actual RUL value for the testing machine/component is also utilized. In the training process, all the available machine measurement data points are used as the training samples, and each data point is associated with its RUL label as the target.

Following the data processing in Section 6.3.2, data normalization techniques are applied. The piecewise linear degradation model (i.e. Section 6.2.4) is used to obtain the RUL label with respect to each training sample. During testing, the one data point corresponding with

Table 6.2 Dataset Information of Training Predictive Maintenance RUL Model

Description	Data
Machines/components for training	87
Machines/components for testing	87
Operating conditions	6
Condition modes	2
Training samples (default)	18,620
Testing samples	100

Table 6.3 Default parameters of the proposed method and the experimental setting

Parameter	Value
Time Window	40
LSTM Layers	3
Neurons in fully connected layer	100
Dropout rate	0.5
Convolution Layers	2
Epoch number	250
Batch size	150

the last recorded cycle for each machine component is generally used as the testing sample. The overall dataset information used for training predictive model is presented in Table 6.2.

Regarding training predictive model, the input refers to the training set and the target outputs are the actual RUL of the training set. The default parameters of training the proposed method are presented in Table 6.3. The time window refers to the amount of time cycles used for each input to the model. The length can be changed to improve accuracy; however, it also influences the number of available samples. The network architecture includes two convolutional layers, three LSTM layers with 100 fully connected layers. The training is performed at 0.5 of dropout rate for combating data overfitting, with the number of epoch (the total amount of training iterations over the complete training set) and batch size (the amount of data samples introduced in training process before each update, also referred as mini batch) at 250 and 150 respectively.

To optimize the training network, the Adam optimizer is used with the learning rate set at 0.001 to achieve stable convergence. The *Keras* library with the *TensorFlow* backend is used for training the model (Goodfellow et al., 2016). The impact of the number of network layer and time window on the proposed network is discussed in Section 6.4.2.3.

6.4.1.2 Performance Comparison

6.4.1.3 Comparison with different methods

To show the effectiveness of the proposed approach, performance comparison with different methods i.e., mostly used network architectures is carried out. Different prognostic methods for RUL estimation are carried out, including basic neural network (MLP), recurrent neural network (RNN), long short-term memory (LSTM) and convolutional neural network (CNN).

- MLP: the basic neural network, which is also known as multi-layer perceptron (MLP). Model comparison is configured with 1 hidden layer of 300 neurons which is a reasonable number in neural network-based approaches (Zhang, Lim, Qin and Tan, 2017). To enhance the generalization ability of neural network, dropout is applied.

- RNN: The recurrent neural network (RNN) is capable of learning time series data and is a more effective model for time-series data, compared with traditional machine learning techniques (Goodfellow et al., 2016). It has the ability of processing dynamic information, that is facilitated by the feedback connections from the hidden or output layers to the preceding layers. In the model setting, 5 recurrent layers in the RNN network, which is similar our hybrid approach, is configured for comparison as well as a fully-connected layer is also attached to have similar architecture with the proposed method. In this way, the two methods have the same depth, and similar computational burden according to the experiments that will be presented in the following sections.

- LSTM: Due to the vanishing gradient problem during back-propagation for model training, traditional RNN suffers from long-term dependencies (Hochreiter and Schmidhuber, 1997). Therefore, as a variant of RNN, long-short term memory method is preferred by many approaches to prevent back-propagated errors from vanishing or exploding (Goodfellow et al., 2016). Gates such as input, output, forget of LSTM enable each recurrent unit to adaptively capture dependencies of different time scales. To share similar structure with the proposed approach, 4 LSTM layers and 1 fully-connected layer with dropout rate of 0.5 are utilized for comparison.

- The convolutional neural network contains two dimensional network layers with one pooling layer. Convolution layers are combined with pooling layers to reduce computation time and to gradually build up further spatial and configural invariance. To achieve similar structure with the proposed approach, 3 convolution layers including pooling layer and 1 fully-connected layer with dropout rate of 0.5 are utilized for comparison.

For all the comparing methods in this study, the input and output layers are the same with the proposed approach in Figure 6.2 in Section 6.3, and *RMSE* is used as the loss function for performance measurement as discussed in Section 6.2.1. Back-propagation is employed for the updates of model parameters where the Adam optimization algorithm is used. The corresponding results are presented in Section 6.4.2.2.

6.4.1.4 Comparison with related works

To evaluate the proposed method effectively, some of the most reported papers of prognostics are identified and the corresponding reported results are compared with the proposed method. The selected related works with methods include:

- Support vector regression (SVR): is a popular data-driven approach for machine learning problems such as classification, etc. (Si et al., 2011). For instance, in the context of classification, SVM searches for the optimal separating hyperplane between the two classes with the maximum margin to the nearest data point of each class, resulting in a high generalization between the two classes. Thus, it offers good generalization, minimizing the structural risk as an advantage (Louen et al., 2013).
- Random forest: is another popular method for traditional machine learning problems, capable of outperforming different machine learning methods, particularly in classification tasks (Si et al., 2011; Zhang, Lim, Qin and Tan, 2017).
- Gradient boost: is another machine learning method for regression, classification and other tasks, which utilizes an ensemble approach to produce a prediction model, typically decision trees. Based on decision tree, the best prediction model is chosen for the learner, which can outperform technique such as random forest (Si et al., 2011; Zhang, Lim, Qin and Tan, 2017).
- Echo state network with kalman filter: the approach is based on RNN for RUL estimation. To improve the estimation precision for amount of data sets with different features, Kalman Filter algorithm is used for training the model (Peng et al., 2012).
- Multi-layer perceptron (MLP): the basic neural network, which is also known as multi-layer perceptron (MLP). The different network layers, often called hidden layers are made up for the basic network to learn (Zhang, Lim, Qin and Tan, 2017).
- Convolutional neural network (CNN): is used for RUL estimation using public available dataset, the turbofan engine data of NASA Ames Prognostics Data Repository (Heimes, 2008; Sateesh Babu et al., 2016).

- Standard LSTM network: uses LSTM for RUL estimation using public available dataset, the turbofan engine data of NASA Ames Prognostics Data Repository (Heimes, 2008; Zheng et al., 2017).

These works utilized publicly available dataset, *C-MAPP* with *RMSE* score for RUL problem. In the implementation of SVR, the radial basis function kernel is used to adapt to the data non-linearity. MLP is constructed using 3 layers of perceptron, with ReLU as the activation function in each layer. RNN follows the same structure as the proposed method, the LSTM cell is replaced by standard RNN cell. The CNN consists of 2 convolutional layers and 2 pooling layers. Finally, the standard LSTM network is constructed with two one-directional LSTM layers.

For evaluation purpose, both the same performance metric, *RMSE* and public dataset utilized in the existing works are applied to the proposed method. The corresponding results are presented in Section 6.4.2.4.

6.4.2 Experiment Results

In this section, the performance of the proposed model for RUL estimation in Section 6.3 is presented in Section 6.4.2.1. The performance results and evaluation including the effects of different factors including the number of hidden layers and time window length are discussed in Section 6.4.2.2 and Section 6.4.2.3 respectively. To demonstrate the effectiveness of the proposed method, performance comparisons with other popular neural network models are carried out and the effectiveness of the proposed approach is demonstrated by comparing with some of the latest state-of-the-art prognostic results in Section 6.4.2.4.

6.4.2.1 RUL Performance

The RUL prediction results of the machine components in the dataset regarding the sequence data point are presented in Figure 6.4. The testing machines/components are organized by the actual RUL values from large to small i.e., the observation and analysis for degradation. From the overall RUL prediction result for the machine/component in the dataset at Table 6.1, the predicted values of RUL by the proposed method are generally close to the actual values of RUL, particularly the prognostic accuracy tends to be higher in the region where the RUL value is small. In this aspect, when the machine component is close to failure, the fault feature is enhanced and that can be captured by the proposed approach for better maintenance analysis.

Furthermore, the RUL estimations for the lifetime of the testing machine components in the dataset before the last recorded cycle are presented in Figure 6.5, Figure 6.6, Figure 6.7,

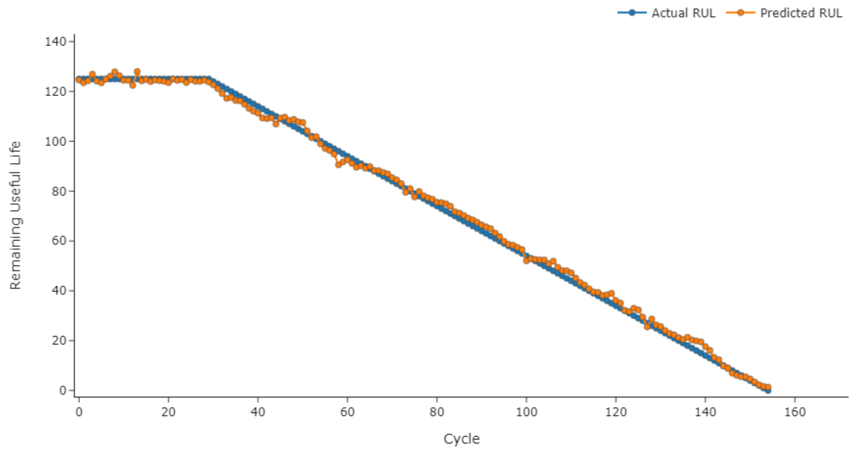


Fig. 6.4 RUL prediction result for the machine components in the dataset (Sang et al., 2021*a*)

Figure 6.8, Figure 6.9 and Figure 6.10. 6 different cases out of 4 CNC machines with 87 multiple machine components from the dataset, machine components are *5, 11, 24, 37, 59 and 76* are presented for the demonstration of multiple machine components. The actual values of RUL for the last operation cycles are provided in the dataset, and the corresponding RUL labels for the previous lifetime can be attained accordingly.

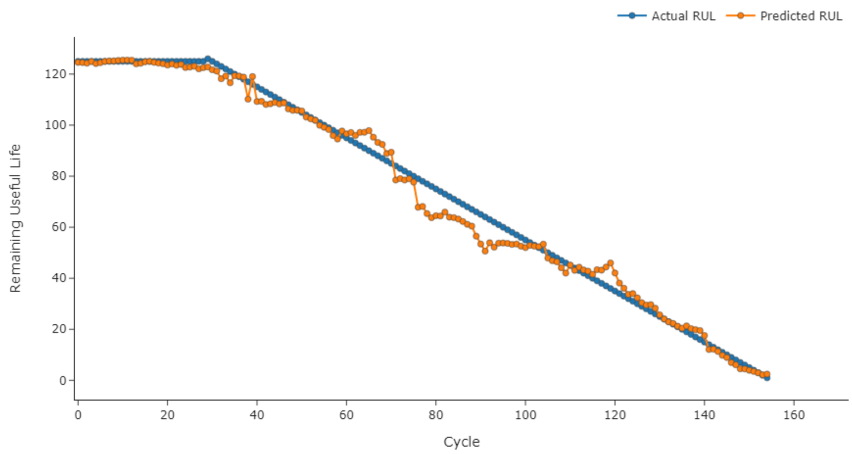


Fig. 6.5 Example of RUL prediction for the testing machine components in the dataset for machine component 5 (Sang et al., 2021*a*)

From the 6 cases, particularly in the early periods in all cases (i.e. Figure 6.5, Figure 6.6, Figure 6.7, Figure 6.8, Figure 6.9 and Figure 6.10) it can be observed that the proposed

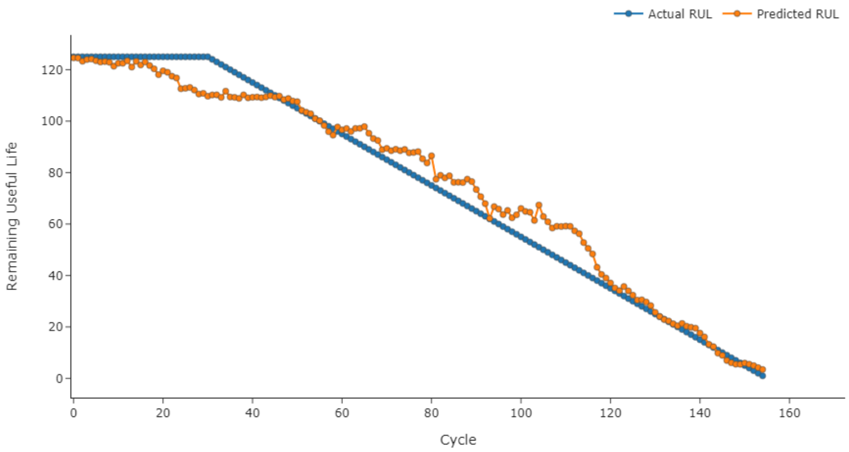


Fig. 6.6 Example of RUL prediction for the testing machine components in the dataset for machine component 11

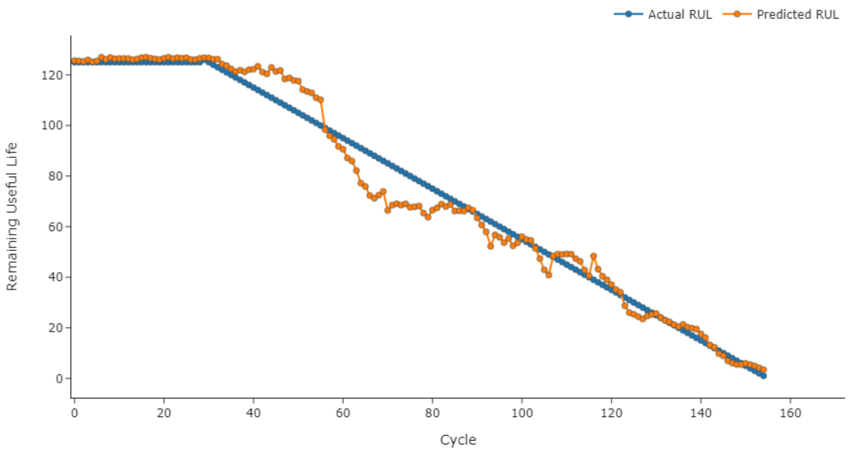


Fig. 6.7 Example of RUL prediction for the testing machine components in the dataset for machine component 24

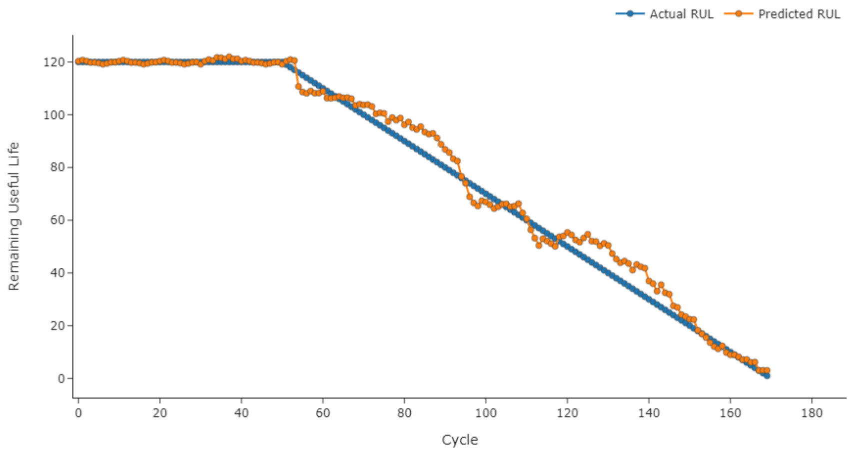


Fig. 6.8 Example of RUL prediction for the testing machine components in the dataset for machine component 37

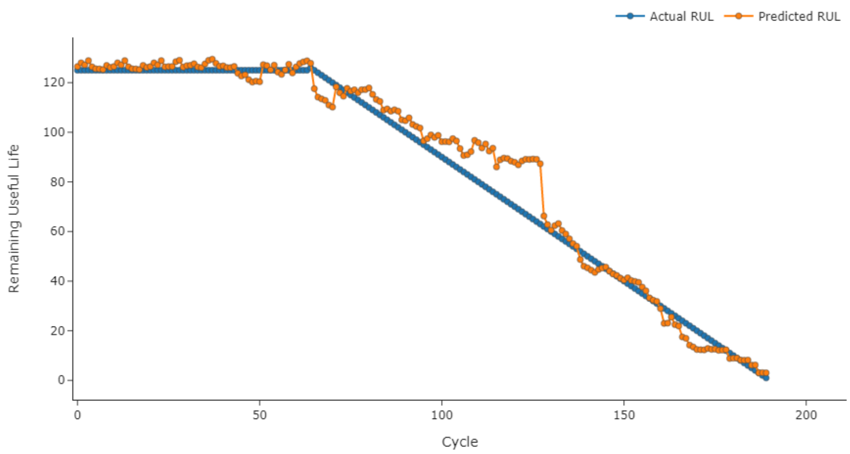


Fig. 6.9 Example of RUL prediction for the testing machine components in the dataset for machine component 59

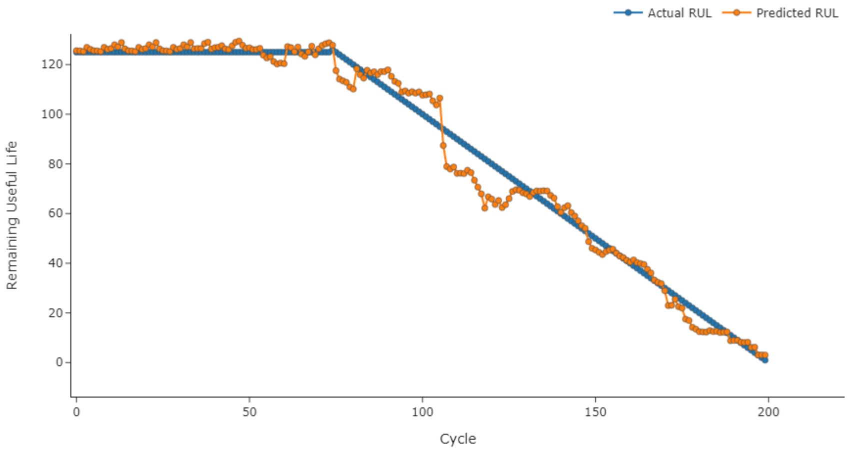


Fig. 6.10 Example of RUL prediction for the testing machine components in the dataset for machine component 76

approach is able to predict the RUL values as close to the actual values. Subsequently, the estimations are almost linearly decreasing over time until the end of the available testing samples. Although, some noticeable gap existing between the predicted and actual values of the RUL in general, the prognostic accuracy is reasonably high, especially when the machine components are close to failure. This is critically important for Industry 4.0 manufacturing such as the application case in effectively managing maintenance, especially in dealing with the late period in the machine component lifetime for complex systems. An effective assessment of the machine component condition in the late period can improve operation efficiency, improve the whole system performance, and ultimately minimize downtime and costs i.e., maintenance, etc.

6.4.2.2 Comparing Performance with Other Methods

Using the described comparison methods in Section 6.4.1.2, the comprehensive comparison results of the prognostic performance are provided in Table 6.4 and Figure 6.11. Using similar experiment settings such as dataset i.e., Section 6.1, Section 6.3, the effectiveness of the proposed method is examined. From the results, it can be observed that the proposed method generally attains the best performance in all the cases.

From the performance results presented in Table 6.4, the proposed model performance, *RMSE* is over *19.35* which is considerably good but better, compared with the others at *38.96, 34.52, 21.11, 22.71 and 19.13* respectively. Notably, the comparing methods *CNN and LSTM* methods perform well at *22.71* and *21.11*, compared with the others two methods

Table 6.4 Performance comparisons of different methods in RMSE (Sang et al., 2021*a*)

MLP	RNN	LSTM	CNN	Proposed Method
38.96	34.52	21.11	22.71	19.13

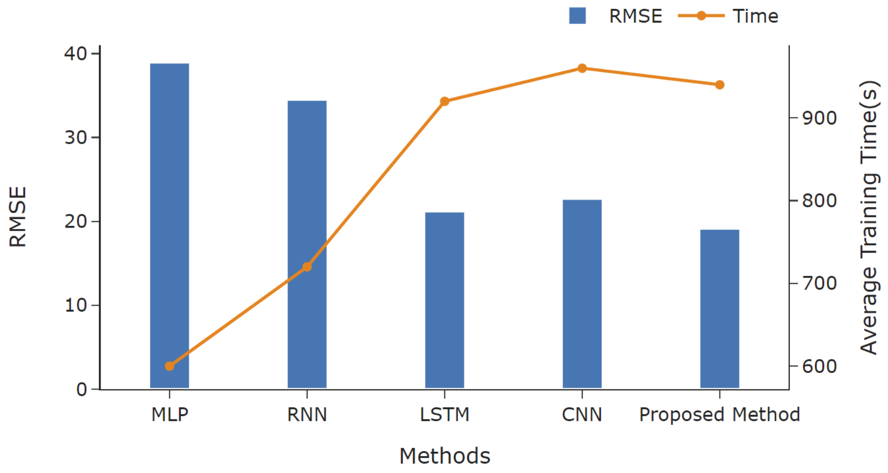


Fig. 6.11 RUL Performance by different methods (Sang et al., 2021*a*)

at *38.96* and *34.52*. These two methods could provide potential solutions for different dataset i.e., image for CNN as well as sensor data with minimal additional data such as condition. Moreover, the proposed method could well be improved with new sample data as well as parameter tuning.

From the experimental results, it indicates that the proposed hybrid deep neural network architecture works well with RUL estimation for prognostic problem, specifically in the context of Industry 4.0 manufacturing such as the application case. The convolution layers contribute to the learning capability of the network. The RNN structure is the second best using the recurrent information flow. While LSTM is a more advanced variant of RNN, its performance also outperforms RNN in this case study. However, it can be further optimized to get better results. The basic neural networks MLP and RNN are the least effective ones. CNN, LSTM, and the proposed method are the most competitive methods in this instance. That suggests that the sample preparations with raw feature selection including sensor data of multiple machine components, data pre-processing and application of time window are efficient for further feature extraction.

Traditionally, deep neural network learning suffers from the overfitting problem (Goodfellow et al., 2016). By applying regularization technique, i.e. dropout, good performance is obtained in this study. Moreover, it can be observed that the *RMSE* scores of MLP and RNN are relatively higher because of their limitations of computation memory and complex sensor data. This is due to the increased number of multiple machine component's data including operation and condition which makes the prognostic problem more complicated. On the other hand, overfitting has large opportunity to occur with the increased number of sensor data as well as machine component. In this case, further works including sensor data fusion and optimized processing, etc., will provide an additional enhancement to our approach, especially in dealing with more complex datasets from Industry 4.0 manufacturing.

In summary, based on the presented results i.e. Figure 6.4, Figure 6.5, Figure 6.6, Figure 6.7, Figure 6.8, Figure 6.9, Figure 6.10,Table 6.4, Figure 6.11, it demonstrated that the proposed method is promising for prognostic problems and is able to provide reliable RUL estimations in different cases. Acquiring accurate RUL information of the machines/components in the later stage of its lifetime could well lead to providing actionable information for effective maintenance management and subsequently reducing downtimes and costs. In this instance, the predictive maintenance service i.e. *MPMMHDLA* model as an embedded FIWARE component on the *PMMI 4.0* platform, can be accessed via the NGSI API by the users i.e. maintenance engineer or manager. And the RUL values of the machine/component are then available for the decision makers in their maintenance schedule plan.

As our approach supports the aspect of modular and hybrid method as described in Section 6.3, Section 6.3.5 and Figure 6.2, the proposed model as well as other best performance models such as LSTM, CNN, can be considered for deployment on the *PMMI 4.0* platform, particularly in dealing with the optimization of the model utilizing new dataset (i.e. the whole factory business operation including systems/components is beyond the scope of the available dataset for this work), etc. The model information such as model configurations/parameters, dataset and features, performance metrics, etc., can be stored in the model repository so that new optimized model can be evaluated, compared, and deployed as illustrated in Figure 6.2, part of the proposed *PMMI 4.0* in Figure 5.4 in Chapter 5. In this way, continuous optimizations can be achieved upon new dataset e.g., new sensor data of different machines/components, etc., or new model configurations, etc., in a dynamic and modular manner.

The performance analysis i.e., impact of neural network layers and time window to the proposed method is presented in the next section.

6.4.2.3 Impacts of hybrid neural network layers and time window

In this section, the influence of the key parameters in the proposed approach is analysed. In this context, the same dataset i.e., Section 6.1, Section 6.2 is used and explored with

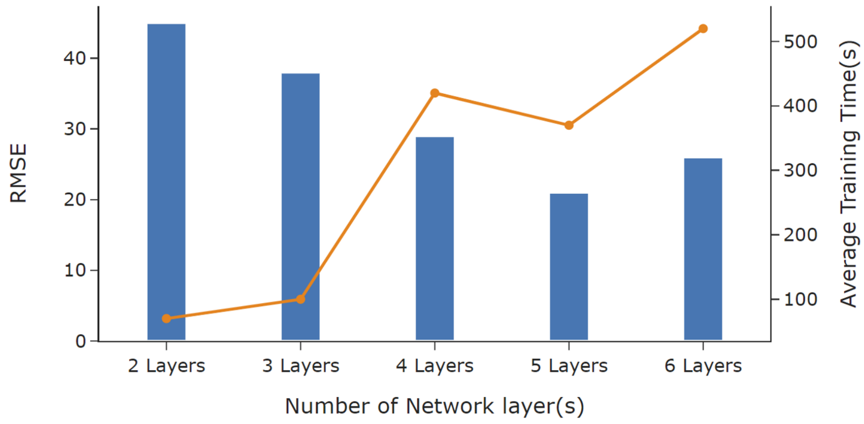


Fig. 6.12 Relations among neural network layers, RUL performance, and training times

different settings i.e., network layers, time window for evaluation. First, the impact of the neural network layers setting on the network prognostic performance is presented in Figure 6.12 whereas the left *y-axis* column presents the score of *RMSE* for each instance, the *x-axis* represents the number of network layers i.e. Convolutional and LSTM network layers, and the right *y-axis* column presents the average training time (in seconds). The setting of network layers is configured as: *2 layers (1 Convolutional layer + 1 LSTM layer), 3 layers (1 Convolutional layer + 2 LSTM layers), 4 layers (2 Convolutional layers + 2 LSTM layers), 5 layers (2 Convolutional layers + 3 LSTM layers) and 6 layers (3 Convolutional layers + 3 LSTM layers)*.

From the results in Figure 6.12, it can be observed that more layers i.e., convolutional and LSTM, lead to lower scores of RMSE generally. This suggests the deep neural network architectures more information than the shallow neural network architectures. However, high prognostic accuracy gaining from higher network architectures suffers from computation time, increasing almost linearly with the hidden layer number. In general, it is observed that the experiment network with *5 layers (2 Convolutional layers + 3 LSTM layers)* obtains the overall good performance with average computing burden, compared with the other network settings. Hence, the *default number of neural network layers* in the proposed approach in this work is set to *5 layers (2 Convolutional layers + 3 LSTM layers)*.

Furthermore, the *time window size* in the sample data preparation as described in Section 6.3 is another important aspect in the proposed approach. In this instance, sequence or time series sensor operation data are part of the factory maintenance related machine equipment tools. Different time window sizes can influence the whole process of managing maintenance activities. However, choosing time window should reflect on the business problem and available datasets. For this experiment, the range of the time window size $N_t w$

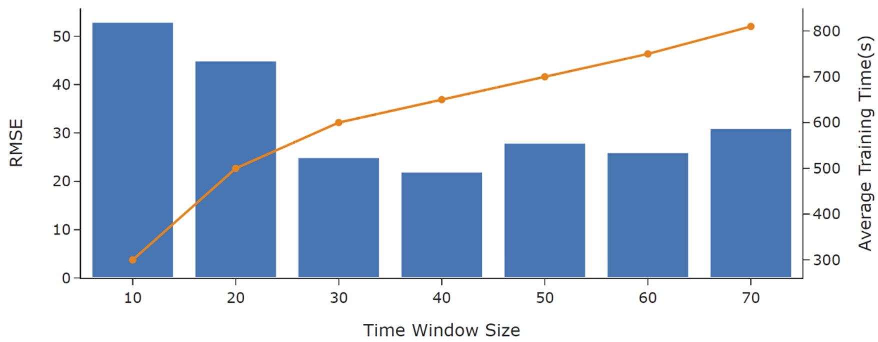


Fig. 6.13 Relations among time window sizes, RUL performance, and training times

are set from 10 to 70 for analysis. In the testing dataset, the machine components have different operation cycles i.e., different length.

For a more comprehensive analysis of the time window sizes on the network performance, the testing machine/components with shorter operation cycles than the set $N_t w$ are not considered for the analysis. It should be noted that in the testing set, the data operation cycles for the testing machine/component have different length, and the shortest one has only 27 operation cycles. Thus, the testing machines/components which have shorter operation cycles than time window is not included in the respective cases. The impact of the time window sizes on the network performance is presented in Figure 6.13.

From the analysis results in Figure 6.13, it shows that better performance i.e., RUL estimation is obtained with higher $N_t w$ results. With further information/dataset applying feature extraction and processing, larger time window can be covered, and that will offer further analysis cases for the prognostic problem. Particularly, a significant decrease in RUL estimation error exists when $N_t w$ increases from 40 to 50 in the prognostic performance, and however no substantial improvement is gained when $N_t w$ exceeds 40. It can also be observed that the second-best performance is achieved at $N_t w$ 30, which is lightly higher in error but is relatively good, compared to the other time window sizes.

Similar with the effect of the network layer number in Figure 6.12, the overall computation of the training process is significantly impacted by the size of $N_t w$. From the analysis results in Figure 6.13, it shows that the computation burden becomes widen as the size of $N_t w$ increases. As previously stated, the analysis results do not include all possible time window sizes (i.e., ignore operation cycles less than 27) in the whole testing dataset. Upon acquiring further information/dataset, different patterns/sizes of the $N_t w$ can be reflected. Overall, based on the available dataset information and the experiments with the corresponding results, $N_t w$ 40 is utilized the default setting, and $N_t w$ can be determined accordingly.

Table 6.5 RMSE results using different predicative methods

Method	RMSE
Support vector machine - SVR (Louen et al., 2013)	29.82
Random forest (Zhang, Xiong, He and Shen, 2017)	31.12
Gradient boosting (Zhang, Xiong, He and Shen, 2017)	30.01
Echo State Network with Kalman filter (Peng et al., 2012)	29.46
Multi-objective deep belief networks ensemble (Zhang, Xiong, He and Shen, 2017)	28.66
CNN (Sateesh Babu et al., 2016)	26.01
LSTM (Zheng et al., 2017)	25.57
Proposed Method	24.26

6.4.2.4 Performance results with related works

Furthermore, the effectiveness of the proposed method is also compared with some of the most reported works with related methods i.e., deep learning approach focusing on RUL estimation. These existing works mostly used publicly available dataset i.e. C-MAPSS (Ramasso and Saxena, 2014). For the evaluation purpose, we utilize the same dataset, specifically *FD003* for this instance since it includes additional data such as setting. Table 6.5 summaries the reported results (of the existing works) against the proposed method. It can be observed that many neural network-based approaches have shown their merits on this prognostic problem, including LSTM, CNN, etc. as well as traditional approach such as SVR, Random forest, etc.

From the performance results in Table 6.5, our approach achieves promising advantage, compared with the results of the state-of-the-art approaches. In the experiments, the RUL threshold is set to the condition of the system which can have different effects on performance. Though the proposed method has an increase value of the RMSE for the RUL estimation, compared with the application case experiment in Section 6.4.2, the outcome is still competitive, as shown in Table 6.5. For further analysis, additional explorations such as different period of the constant RUL value or parameters tuning can be carried out. While different methods are employed in different studies, the presented results in Table 6.5 are still able to provide a general comparison of the advanced approaches.

In addition, while LSTM algorithm such as Zheng et al. (2017) is usually preferred in many tasks for sequential signal processing, its computational burden is relatively high with similar network depth. The proposed method can achieve the prognostic results, slightly higher than LSTM and is considered for both high sensor data i.e., operation, condition, etc., of multiple machine components with a hybrid architecture approach, and similar or lower computing load. Thus, the proposed method is promising for RUL prognostic task.

6.5 Chapter Summary

In this chapter, we looked at Predictive maintenance for RUL model based on data-driven approach, considering multiple machines components involved in the context of Industry 4.0 as well as the flexibility that facilitates managing the predictive RUL model in a dynamic modular manner.

- Section 6.3 presented a *Modular Predictive Maintenance Model using Hybrid Deep Learning Approach (MPMMHDLA)*, a predictive maintenance model for RUL based on data-driven approach. MPMMHDLA supports the flexibility in dealing with complex systems and dynamic nature of Industry 4.0 in a modular fashion.

- Section 6.2 presented Predictive maintenance RUL problem that is formulated for machines/components involved in the context of Industry 4.0 manufacturing. Data collected from the machine equipment tools in Industry 4.0 manufacturing are diverse and high sequential. Traditional approaches such as HMM as well as deep learning approaches such as RNN suffer from computation as well as storage, particularly in dealing with sensor/time-series data.

  The proposed *MPMMHDLA* is thus based on deep learning approach which is composed of different layers i.e., convolutional, LSTM, in a hybrid manner for better processing of multiple machine/component's operation sensor data and condition data. Factory's machine/component operation/condition data are fed into the convolutional layer for assisting in optimization of high sequential sensor data which then can be mapped into LSTM layer that provides optimized time-series data processing.

- Section 6.4 demonstrated and verified *MPMMHDLA* using FIRST's industrial dataset. For evaluation, the *RMSE* score function is utilized and comparison analysis with different methods such as standard CNN and LSTM is performed. Based on new data or business needs, our approach *MPMMHDLA* allows different model configurations/parameters or new dataset for the optimization of the predictive maintenance RUL model in a dynamic and modular manner.

  Furthermore, the proposed method is compared with some widely reported related work using a public dataset and performance measurement. In all cases, *MPMMHDLA* offers higher accuracy and result i.e. RMSE at 19.13%.

The contributions including journal/paper publications of this chapter include:

- A Modular Predictive Maintenance Model using Hybrid Deep Learning Approach *MPMMHDLA* for RUL estimation
- Supporting modular model for *MPMMHDLA*, in dealing with complex systems and dynamic nature of Industry 4.0
- Design a new prognostic for FIRST datasets, applying *MPMMHDLA*
- Implement different modules of *MPMMHDLA* in FIWARE for different prognostics
- Sang et al. 2020. Towards Predictive Maintenance for Flexible Manufacturing Using FIWARE. CAiSE 2020, Advanced Information Systems Engineering Workshops. Lecture Notes in Business Information Processing, vol 382. Springer (Sang, Xu, de Vrieze and Bai, 2020*b*)
- Sang et al. 2021. A Predictive Maintenance Model for Flexible Manufacturing in the Context of Industry 4.0. Frontiers Journal. doi: 10.3389/fdata.2021.663466 (Sang et al., 2021*a*)

Chapter 7

Predictive Maintenance Scheduling

Based upon the modular predictive model, *MPMMHDLA* presented in Chapter 6, an approach to predictive maintenance scheduling can be created. This chapter analyses the requirements for such an approach, evaluates various options and proposes an approach that is tailored towards the needs of Industry 4.0. Maintenance related information such as maintenance, machine, schedule, etc., are accessed and processed using the proposed data model in Figure 5.2, *Data Model for Predictive Maintenance for Industry 4.0* along related maintenance databases of *PMMI 4.0* in Figure 5.4 in Chapter 5. This chapter contains the published Journal 1[1], Paper 4[2], and Paper 3[3].

For effective predictive maintenance in a complex manufacturing context, data-driven predictive model i.e., RUL driven by operation/condition data of the machine equipment tools, instead of model-driven (i.e., driven by domain knowledge and experts) drives the maintenance scheduling process that assists maintenance decision making. In this context, the aspect of Industry 4.0 i.e., multiple machine components, must be considered.

Industry 4.0 driven manufacturing systems are complex systems of strongly interconnected machines or devices who interact and collaborate for business processes towards common goals (Koren et al., 2018; Thoben et al., 2017; Zezulka et al., 2016). For any predictive maintenance scheduling, any activity to be performed in such complex systems should hence consider for the various machine components operated. A concrete predictive maintenance schedule strategy is thus essential for operation in a complex manufacturing system.

[1] Sang et al. 2021. A Predictive Maintenance Model for Flexible Manufacturing in the Context of Industry 4.0. Front. Big Data 4:663466 (Sang et al., 2021*a*)

[2] Sang et al. 2021. Supporting Predictive Maintenance in Virtual Factory, PRO-VE 2021 Smart and Sustainable Collaborative Networks 4.0, 22-24 November 2021 (Sang et al., 2021*b*)

[3] Sang et al. 2020. PRO-VE 2020 Applying Predictive Maintenance in Flexible Manufacturing. Boosting Collaborative Networks 4.0. (Sang, Xu, de Vrieze and Bai, 2020*a*)

Traditionally, Manufacturing Execution Systems (MES) are utilized for scheduling operations such as maintenance (Pinedo, 2016). MES normally operates within one manufacturing system and thus, lacks the support for flexibility and scalability in dealing with complex systems. In Industry 4.0 manufacturing context, predictive maintenance scheduling is challenging as it associates with various linked systems and machine equipment tools such as CPS, Robots, CNC machines, etc. In the case of traditional maintenance, Chan and Asgarpoor (2006); Wang (2002) mostly focus on the aspect of single-component systems and hence overlook the associated machines components. The focus of various works including Dekker et al. (1997*a*,*b*); Van Horenbeek and Pintelon (2013) turn towards the aspect of multi-component systems. In this context, a machine equipment with more than one component was considered. Also, additional considerations such as economic such as cost related to downtime, machine, are recognized by Dekker et al. (1997*a*).

Furthermore, several existing works from Mourtzis et al. (2017), Senra et al. (2017), Levrat et al. (2008) generally utilize data gathered from factory operation i.e., state i.e. failure event, threshold of regular maintenance, etc., of machine equipment, production plan, etc., and use it for maintenance planning. However, these approaches mostly focus on reactive or prevent maintenance and do not consider the aspect of predictive maintenance and complex systems. Moreover, these existing approaches mostly focus on model-driven i.e., driven by the physical degradation state of machine equipment or domain experts, for maintenance (i.e., preventive), and lack the consideration for the applicability of multiple machines/components driven by predictive models and the schedule plan for producing new predictive maintenance schedule, especially in the context of Industry 4.0.

Based upon the challenges described above as well as the key issues discussed in Section 2.4.4, Section 2.5, it is clear that an optimized approach is needed for dealing with the maintenance schedule problem of complex systems in Industry 4.0. The optimized approach should consider the nature of complex systems i.e., complex systems, multiple machine components involved in Industry 4.0 focusing manufacturing. Since traditional techniques such as reactive and preventive cannot deal with the complexity and demands of Industry 4.0 domain (Koren et al., 2018; Mobley, 2002; Tobon-Mejia et al., 2012; Zezulka et al., 2016), the optimized approach utilize a data-driven method. Essentially, data driven predictive maintenance schedule is based on predictive maintenance models that are built using machine learning or deep learning techniques and the historical, operational and condition data of the machine equipment. Predictive maintenance models are deployed and consumed for the detection of pending failure of the machine equipment, assisting better maintenance (Mobley, 2002; Pinedo, 2016).

Thus, *Predictive Maintenance Schedule for Industry 4.0 Multiple Machines and Components (PMS4MMC)* is proposed for a way of supporting a data-driven predictive maintenance scheduling in the context of Industry 4.0. The contributions include:

- To investigate Industry 4.0 predictive maintenance scheduling for a series of machines within a product line for a flexible manufacturing, utilizing a predictive model and decision-supported maintenance schedule plans for multiple machines/components involved in complex manufacturing, specifically in the context of Industry 4.0 predictive maintenance.
- To present an optimized decision method for scheduling predictive maintenance activities, utilizing the modular predictive maintenance RUL model and a data-driven predictive approach. An effective predictive maintenance schedule should also consider the cost related with the predictive maintenance schedule activity the scheduled task as well as the cost over the period for predictive maintenance task. Essentially, the goal of the predictive maintenance scheduling is to achieve an optimal way of minimizing the overall predictive maintenance cost, considering multiple machine components with associated maintenance tasks, operation or downtime time and the optimal time for maintenance to be carried out.
- To support a modular approach in dealing with complex systems and dynamic nature of Industry 4.0 as well as the different maintenance aspect such as tasks, maintenance cost, as well as the availability of resource such as availability status of each components, engineer, etc., potentially in a prescriptive manner.
- Using the proposed *PMS4MMC* with *MPMMHDLA* (i.e., chapter 6) and PMMI 4.0 (i.e., chapter 5) to apply to industrial cases including a Flexible Manufacturing and a Virtual Factory of the FIRST project for verification.

In this section, *Predictive Maintenance Scheduling Optimization for Industry 4.0* including traditional approaches with their challenges as well as different key factors which should be considered for Industry 4.0 predictive maintenance scheduling optimization is presented in Section 7.1. Adopting the approach along with identified factors, data-driven predictive maintenance schedule driven by predictive model supporting multiple machine components, *PMS4MMC* is proposed in Section 7.2. In Section 7.3, the proposed method is implemented with *MPMMHDLA* and validated using the FIRST Project industrial cases including flexible manufacturing and virtual factory, and the performance evaluation and comparison with existing approaches is presented. A summary of the chapter and the contributions are provided in Section 7.4.

7.1 Predictive Maintenance Scheduling Optimization for Industry 4.0

Industry 4.0 predictive maintenance must consider the multiple machine components involved in operating the factory operation. Separate maintenance for each of the multiple machine components at different times can be highly expensive since there are different challenges such as the resource availability of each machine component, the type of each maintenance i.e., repair, or replacement and the setup cost of each maintenance i.e., shutdown and up, engineer (Mobley, 2002). Considering the availability of maintenance resources such as engineers, tools, spares, etc., whilst coordinating potential pending failures of the machine equipment within a time window is much desired.

In this section, we look at existing approaches for maintenance scheduling optimization in Section 7.1.1 and different key factors (i.e., derived from the challenges of the existing approaches) considered for predictive maintenance scheduling optimization in the context of Industry 4.0 is discussed in Section 7.1.2. The key factors identified are used for designing the proposed *PMS4MMC* solution.

7.1.1 Approach for Industry 4.0 Maintenance Scheduling Optimization

Industry 4.0 driven manufacturing systems are *complex systems of strongly interconnected machines or devices* that interact and collaborate for business processes towards common goals (Koren et al., 2018; Thoben et al., 2017; Zezulka et al., 2016).

Over time, the condition of the factory machines is hampered by the usage and age. This eventually leads to deficient operation or a machine failure if no maintenance action is taken (Mobley, 2002). Maintenance activities are hard and expensive (Mobley, 2002; Sang et al., 2021*a*). Ultimately the failures of the machine equipment tools impact the entire manufacturing network and may result in undesired downtime and costs (Sang et al., 2021*a*). Furthermore, the excessive or unnecessary maintenance caused by the machine failure can contribute to the overall maintenance downtime and cost (Mobley, 2002).

In a complex manufacturing setting, there exist dependencies of various machine components which operate in manufacturing and factory process. For an effective predictive maintenance, any activity related maintenance should consider the nature of complex systems i.e., multiple machines components. Thus, an effective approach for dealing with such complex systems is critically important for Industry 4.0 focusing manufacturing.

In general, maintenance scheduling is a process that optimizes the resource and capacity required for the maintenance and related activities. The process can be based on either constraint such as start, end and duration of the maintenance activity or a more coordinated process of the maintenance activity and job simultaneously. Manufacturing Execution Systems (MES) are often used for the scheduling of manufacturing operations (Pinedo, 2016). MES however is not efficient in dealing with diverse and complex systems in a collaborative network due to the demands of increasing flexibility and scalability. This shows that there is an opportunity for flexible approaches that supports managing the manufacturing process efficiently for complex manufacturing.

In Industry 4.0 manufacturing, maintenance is challenging as it associates with complex systems and machine equipment tools e.g., CPS, IoT, Robots, CNC machines. Different aspects of maintenance have been explored in the research community. In the case of traditional maintenance, single-component systems were mainly explored (Chan and Asgarpoor, 2006; Wang, 2002). These approaches mostly focus on model-driven approach which is driven by the physical degradation of the machine tool, assisted by domain experts for preventive i.e., regular/routine maintenance. Particularly, both methods only consider for single machine or component and overlook the related machines/components. Thus, the aspect of multi-component systems maintenance become the focus of various works (Dekker et al., 1997*a*,*b*; Van Horenbeek and Pintelon, 2013). In this context, a machine equipment with more than one component is considered and the approach is described structure dependence. *Structural dependence* refers to the structural, static relationships between different components of a machine . In the context of maintenance, structural dependence is considered for a case where the replacement of a certain component requires the replacement of other components, the case in which a component is stopped due to failure or maintenance of another component. Maintenance (i.e., reactive or preventive) is based on the model driven by the structure of the different components associated with a machine, and maintenance can be costly.

To optimize the aspect of maintenance cost, *economic dependence* (or opportunistic for grouping) is introduced by Dekker et al. (1997*a*). In this context, utilizing model driven by structure dependence, the maintenance of different components is grouped for saving maintenance cost. This approach can make huge impact on cost saving when maintenance is associated with high costs (e.g., multiple engineers required for several tasks, production downtime due to several maintenance activities, etc.). On the other hand, maintaining several components simultaneously may lead to higher costs than maintaining them separately due to different constraints such as production losses, safety requirements, or systems with restrictions such downtime, engineer, etc.

The deterioration or failure process of a machine component can also impact the other components operating in production. This approach is described as *stochastic dependence* by Van Horenbeek and Pintelon (2013). If a component fails, the system keeps operating but the remaining components structurally need to work harder to realize the same output level. Essentially, the failure or inefficient process of a machine component may cause damage to other components, leading to an increase of the deterioration level or even an instant failure of these components. At this stage, the aspect of structural, economic, and stochastic dependence generally focuses on model driven approach whereas the physical degradation of the machine component or domain experts is utilized, and maintenance schedule plan is mostly intended for reactive or preventive (i.e., regular, planned, routine) activities.

Mourtzis et al. (2017) present an integrated system, under the concept of Industry 4.0. The approach focuses on the availability of timeslot for maintenance schedule which is facilitated by the data gathered from the monitored equipment. Senra et al. (2017) put forward a schedule process that is based on available equipment with support technicians as well as related processing times. They illustrated the approach using a case study. The approach however lacks the aspect of equipment monitoring for analytics. For production maintenance synchronization, Levrat et al. (2008) present a decision-making tool. It is based on multiple criteria such as product performance and component reliability for producing an optimal scheduling plan. For job shop scheduling, ZHENG et al. (2013) present a scheduling method that incorporates a condition-based maintenance for producing an optimal solution. Generally, these methods use limited data-driven approach for the aspect of maintenance scheduling, however, they lack the consideration for predictive maintenance driven by predictive models as wel as the applicability of Industry 4.0, especially in dealing with multiple machines/components, and the overall schedule for producing new maintenance schedule.

Overall, existing studies focus on maintenance scheduling optimization for one single machine, and have limited attempts of multiple machine components, specifically in the context of Industry 4.0. And these studies focus on maintenance aspects such as structure (structure of the machine), stochastic (machine failure degradation effecting other machine) and economic maintenance (opportunistic for grouping) optimizations that explore in the context of preventive or reactive maintenance. The aspect of predictive maintenance and Industry 4.0 are still to be addressed.

Based on existing approaches as well as the key issues discussed in Section 2.4.4, it is clear that there is an opportunity for predictive maintenance scheduling which considers different factors such as predictive maintenance by data-driven predictive model, multiple machines components, and dependencies such as availability of resources (e.g. engineer) in the context of Industry 4.0.

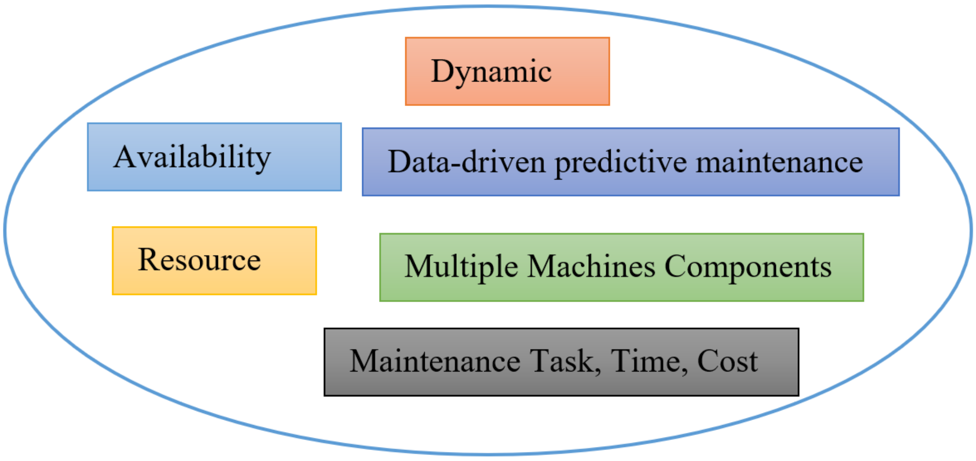


Fig. 7.1 Key factors in optimal maintenance scheduling

7.1.2 Factors Considered for Predictive Maintenance Scheduling Optimization in the context of Industry 4.0

Industry 4.0 manufacturing networks e.g. virtual factories are not restricted by the physical co-location or long-term collaborations (Debevec et al., 2014). The variability of different solutions/virtual factory models and how to adapt the potential solutions/virtual factory models, as well as to upkeep and maintenance of various models and tools are challenging for a collaborative manufacturing network environment. And modern collaborative manufacturing network is complex, and involves modern plant-run machines deployed smart sensors, and robots running on the shop floor as well as a network of collaborations including collaborative business processes e.g. different systems, multiple collaborative partners such as suppliers, manufacturers, designers, customer, etc. Thus, they face different challenges due to the complexity and dynamic nature of the industry collaboration environment. To overcome some of the challenges, advanced capabilities such as predictive maintenance analytics are critical (Sang, Xu, de Vrieze, Bai and Pan, 2020).

Handling the demands i.e. highly collaborative complex systems i.e. multiple machines components of Industry 4.0 focusing manufacturing is challenging (Thoben et al., 2017). From the challenges of existing approaches for Industry 4.0 as previously described in Section 7.1.1 as well as Section 5.1.1 in Chapter 5, several key factors need to be considered for an optimal maintenance schedule plan of *PMS4MMC*. This includes data-driven maintenance i.e., predictive models such as RUL, multiple machine components, the different maintenance aspect such as tasks, maintenance time, cost, as well as the availability of resource such as availability status of each components, engineer, etc. as depicted in Figure 7.1.

7.1.2.1 Data-driven predictive maintenance

Data-driven predictive maintenance refers to the utilization of collected big data for building predictive models such as RUL (predictive RUL is adopted in this work as described in Chapter 6) that facilitate advanced detection of failures/degradation of factory assets. Model-driven approach is widely used by existing approaches as discussed previously in Section 7.1.1. It relies on the physical degradation of the machine equipment tool as well as domain experts for building the model. For the case of Industry 4.0, the complexity of systems and processes make it hard for modelling and application. Moreover, model-driven approach is mostly utilized for traditional maintenances such as preventive and reactive, which act upon failure events or routinely planned schedules. This results in undesired downtime as well as associated maintenance costs including engineer, tools, etc.

For our approach, data-driven predictive maintenance is considered. The approach is driven by predictive maintenance models that are built using historical operation and condition data of the machine equipment tools. Based on predictive maintenance models, advance detection of potential failures can be inspected and timely and appropriate maintenance can be performed. This leads to an effective way of managing maintenance schedule using the predictions as well as other maintenance information. Existing approaches described in Section 7.1.1 as well as Section 5.1.1 in Chapter 5 utilize the production and factory information for assisting in creating maintenance plan, particularly for preventive activity. These approaches do not consider for the utilization of predictive models as well as the nature of Industry 4.0 whereas various machine equipment tools produce large amount of operation sensor data which can be used for building models assisting predictive maintenance scheduling. This requires utilizing state of the art approaches such as the proposed predictive RUL model, *MPMMHDLA* utilizing deep learning in Chapter 6 for handling complex sensor operation data of multiple machine equipment tools involved in Industry 4.0 as our proposed approach in Figure 5.4 in Chapter 5.

7.1.2.2 Resource

Resource refers to the general resources such as engineers, spares, tools, etc., required for the maintenance. In the context of existing approaches, different aspects of maintenance have been studied. The structural aspect is based on the physical structure of one machine. The degradation process of a machine component as described as stochastic. The aspect of economic focuses on cost-saving by grouping maintenance activity. In this work, the resource aspect is realized by considering different resources required in the maintenance optimization. Resources may include maintenance operation of the machine equipment with associated components, processes, engineer, operator as well as associated cost regarding the network chain. Conducting maintenance activity and execution require these resources as a whole system.

In the context of multiple machine components, dependencies such as structural, stochastic, economic should be carefully considered. Structural dependence refers to instance when the repair or replacement of a machine component needs other components to be dismantled or replaced (Dekker et al., 1997*b*). Stochastic dependence refers to the deterioration process of one machine/component is dependent on the state of one or more other machine components (Van Horenbeek and Pintelon, 2013). Economic dependence applies when the combined maintenance of several components leads to a different cost than maintaining each component separately (Nicolai and Dekker, 2008). In our approach, we consider resource (resource dependence) applies when multiple machines/components rely on a shared set of spares or tools, or a limited number of maintenance workers.

Industry 4.0 collaborative manufacturing network is complex, and involves modern plant-run machines deployed smart sensors, as well as a network of collaborations including multiple collaborative partners such as manufacturers, suppliers, etc. (Sang, Xu, de Vrieze, Bai and Pan, 2020). Moreover, collaborative manufacturing networks e.g. virtual factories are not restricted by the physical co-location or long-term collaborations (Debevec et al., 2014). The variability of different solutions/factory models and how to upkeep and maintenance of various models and tools are challenging for a collaborative manufacturing network environment. Thus, maintenance planning becomes harder among the network partners (Sang et al., 2021*b*). Existing approaches, discussed in Section 7.1.1 generally focus on one organization with multiple components of a machine, and the general focus of dependencies such as structure, economic. The resource aspect (e.g., information about maintenance operation of the machine equipment with associated machines, components, processes, operator such as engineer, etc., as well production plan, etc.,) could lead to better maintenance scheduling by providing information about condition of different dependencies i.e., machine, component, production, not just from one manufacturing itself but collaborative manufacturers within the network chain.

7.1.2.3 Availability

Availability refers to the status i.e., availability of the described resources for the maintenance operation. The availability of the resource drives conducting maintenance schedule plan and subsequent execution for the whole system. It is important to get the information of the machine equipment which is required for the maintenance but also to coordinate with other activities/processes e.g., production plan, etc., to schedule optimal maintenance task with minimal impact. At a factory product line, several machines with multiple components may operate for production operation. One or more components might need repair at a certain time which may need to coordinate with the production plan. Moreover, the availability of spares i.e., replacement or repair spare for the maintenance item as well as associated equipment tools dictate the ability to perform the maintenance tasks at given time. Maintenance spares are already in the inventory, otherwise will impact the overall maintenance scheduling. Also, additional complexity arises when certain maintenance tasks require a specific combination of tools i.e., special equipment tools, etc. The maintenance activity can then only be performed if all these tools are available. In case a single tool is required for multiple jobs, a decision must be made with respect to the order in which the components receive maintenance.

The availability for maintenance operation will lead to better maintenance scheduling (Mobley, 2002; Pinedo, 2016). This requires access to related information such as machine, maintenance, production at different product lines, machine, or component levels. In this aspect, the availability of resources for maintenance operation within a factory of Industry 4.0 collaborative network can also be challenging. This means that it requires coordinating with collaborative manufacturers or suppliers, etc., for planning maintenance schedule with the required maintenance resources such as spares, tools, engineers, etc. In Industry 4.0 context, factories may share a pool of the resources to save costs since regular maintenance engineers may have better knowledge and competencies for executing the tasks. Predictive maintenance tasks can only be planned if the required resources, such as spares or tools, are available. Complexity and resource constraint however arise when different factories require factory maintenance, and the resources are demanded, for example, when several components are connected through a shared, limited set of spares that need to meet different requirements such as priority, etc. Consequently, maintenance scheduling optimization will be required on the network system level, rather than the local system level. Maintenance tasks require certain resources that are consumed during the operation. New resources will become available at given time instances, and an optimized maintenance schedule can be achieved given the constraint following from the currently available set of resources.

In this study, the scope of availability covers the general aspect of available resource for the maintenance operation including the maintenance engineer, spares i.e., replacement or repair item, tools i.e., require tools to perform the maintenance, production plan both the factory itself and a collaborative manufacturer. For the network factory, the availability of resource can be accessed, for example utilizing the data model facilitated by FIWARE data adapter in Chapter 5 among the collaborative network chain. The state of the availability applies to existing resources, and lack of inventory i.e., spares or tools or ordering processing is not considered.

7.1.2.4 Multiple machines components

Multiple machines components: Industry 4.0 driven manufacturing systems are complex systems of strongly interconnected machines or devices who interact and collaborate for business processes. In a manufacturing product line, several linked systems, and machine equipment tools including CPS, robots, CNC machines operate towards fulfilling certain manufacturing production goal (Koren et al., 2018; Zezulka et al., 2016). Any failure of these machines can interrupt the whole manufacturing process. To prevent or reduce downtime and costs, an effective maintenance approach that considers the aspect of different key machines' components involved and operated in the manufacturing process is essential.

Industry 4.0 predictive maintenance schedule requires the consideration of multiple machine components i.e., different systems/components e.g. IoT devices, CNC machines, tools, etc. operating in Industry 4.0 collaborative manufacturing. Currently, different aspects of maintenance such as single-component (Chan and Asgarpoor, 2006; Wang, 2002), and multi-component (Dekker et al., 1997*a*,*b*; Van Horenbeek and Pintelon, 2013) systems are predominantly explored in the research community. These studies mostly relied on traditional monolithic manufacturing context, the physical structure of the machine component, expert knowledge for both reactive and preventive maintenances, and most importantly they failed to address the consideration of data-driven approach with multiple machine components in the context of multiple organizations/manufacturing factories in collaborative Industry 4.0 setting.

In a factory operation environment, there may be different settings i.e., different product lines, different type of machine and configurations (i.e., one machine with multiple components or multiple machines). In this context, one product line may operate with multiple unique machines e.g., CNC machine, whilst another product line may operate with multiple machines e.g., robots, CNC machines; some machines may be similar, some machines have redundant one for different productivity, etc. Also, there may exist multiple product lines with either multiple unique machines e.g., robots, or multiple machines with similar machines, etc. (Koren et al., 2018; Thoben et al., 2017).

In this study, we consider the FIRST project industrial case described in Chapter 3. This case includes multiple product lines with different machines such as robots, CNC machines, equipment tools. In a production environment, one product line focuses on producing one part of the material product involving four robots, and another line focuses on cutting or adjusting the produced material from one product line using CNC machines, etc. The different machines, components and equipment tools are connected via sensor devices collecting operation/condition data, as well as are configured specifically for its own product line. Complexity and managing maintenance become challenging as the number of product line and the different types and number of machine equipment tools increase. Traditional approaches such as model-based or experienced-based requires the understanding of the physical structure and degradation process of the complex systems as well as machine expert engineers i.e., possibly different specialized engineers, for an optimized maintenance schedule plan. Moreover, traditional manufacturing system such as Manufacturing Execution Systems (MES) are used for the scheduling of manufacturing operations (Pinedo, 2016) which cannot meet the demands of complex systems involved in Industry 4.0.

In the case of the product line of the flexible manufacturing case, the factory processing system includes three robots, several AGV trolleys, carrier plates with a warehouse, four sets of machines and several machine equipment tools such as coordinate measuring machine as described in Section 3.1. In this study, four different CNC machines with multiple components from the product line are used for experiments in Section 7.3. Thus, the aspect of multiple product lines is considered as future work.

7.1.2.5 Maintenance

Maintenance can be varied, depends on the maintenance task regarding machine equipment can be varied from replacement of a component of a machine equipment to minor or major repairing existing machine equipment which will subsequently impact the associated maintenance time and cost. In the case of maintenance time, it can cover from the preparation time to performing a maintenance task including the time for stopping and restarting the machine, the time for an engineer or operator to perform the task, the time for each machine component repair, replacement, etc.

In a typical predictive maintenance task, the task can be varied. Resolving a failure of a component can be a more significant task, than a predictive maintenance task that might just require readjustment of settings, e.g., setting CNC machine to better cope with a certain production process. Conducting a maintaining task can be increased by accommodating the dependent machine component, e.g., stopping the machine, and restarting it in line with the maintained machine component. The duration of the maintenance time can also depend on the condition status of maintenance task i.e., failure, worn, etc. The condition status, for example a replacement for a breakdown machine component will certainly increase the maintenance time, compared with a worn machine component that might just need a minor repair such as changing a different setting. The sum of these variables can be considered as the overall downtime of a production line that will also impact the whole manufacturing collaboration chain.

For *maintenance cost*, cost minimization is usually the goal of common optimization standards for preventive maintenance. Cost minimization generally aims to reduce the overall maintenance cost. There can be various cost that are subject to conducting maintenance activity. In the context of a manufacturing production line, the cost associated with maintenance may include cost of replacement i.e. buying a new machine/component, production downtime i.e. stopping the production and to resetting the production environment, resource cost including such as the cost of maintenance engineer or team. It is often cost-effective in conducting the maintenance actions of multiple machines/components simultaneously. To achieve the cost-effective option, a typical fixed cost for the maintenance can be considered. In this way, the fixed maintenance cost can be capitalized by focusing on several components at one joint maintenance interval, rather than for a single component that can be targeted in conducting the maintenance activities within a maintenance visit. This may lead to saving the overall maintenance cost for the whole system (Dekker et al., 1997*b*).

For a collaborative Industry 4.0 manufacturing aspect, different machines need to be monitored in multiple organizations within a virtual factor. When scheduling a predictive maintenance plan, the predictive maintenance services can be planned as efficiently as possible, for example, the organizations geographical closed may schedule closer to save time, the similar machines in different organizations which similar conditions may change components at the same period to save costs, etc. One optimal approach is to provide a predictive maintenance schedule which is supported by predictive RUL model incorporating with related maintenance data, that optimizes the overall process related to conducting the required predictive maintenance and thereby reducing the overall cost. The goal of the predictive maintenance activity i.e., short, medium, or long term may become important, depending on the degree of the activity, time, and cost.

Existing approaches such as Dekker et al. (1997*b*), Dekker et al. (1997*a*), Van Horenbeek and Pintelon (2013) as discussed in Section 7.1.1 still overlook the aspect of the resource constraint, thus in this study, to saving the overall maintenance associated cost, grouping maintenance derived from the economic dependence (Dekker et al., 1997*b*) is considered. In this aspect, the associated costs for the maintenance operation of the machines with associated components, setup, resource such as engineer, operator, etc., as well as downtime cost within the network chain, can be minimized by grouping the maintenance items with available maintenance timeslots pending the availability of the resources i.e., the maintenance machine/component (individual repair or replacement), engineer, tools, etc.

7.1.2.6 Dynamic predictive maintenance

Industry 4.0 manufacturing networks are complex and dynamic due to demands i.e., production life cycle, competition, etc. (Thoben et al., 2017). Optimization of factory machine equipment tool is critically important as it can have a huge impact i.e., downtime, cost, etc., on the collaborative network processes and partners (Mobley, 2002; Sang, Xu, de Vrieze and Bai, 2020*a*).

Predictive maintenance supports effective collaborative factory operation as it offers the opportunity to act before any event occurs and hence the impact i.e. downtime, cost, etc. can be avoided or minimized (Mobley, 2002; Sang, Xu, de Vrieze and Bai, 2020*b*). This requires better control and operations to adapt in real time and in response to constant demands, particularly assisting in creating effective maintenance schedule plan for decision making. To support better managing of the complexity and dynamic aspect of Industry 4.0 predictive maintenance, it requires advanced data processing and tools for acquisitioning and processing diverse data from both internal and external sources; data generated by different machine equipment tools, systems and processes, data from networked partner organizations at production and inventory levels, changing consumer demands, and advanced machine learning and optimization techniques for producing information. In other words, it means that taking advantage of various factory operation/condition sensor data by developing predictive models incorporating with the different maintenance related information such as machine and production plan, resource such as engineers, etc., which is then can be utilized for assisting maintenance decision making in a dynamic manner.

In this study, predictive maintenance scheduling deals with multiple inputs such as predicted RULs with different period, maintenance cost and resource availability. Thus, efficiency is of important for supporting dynamic predictive maintenance to better managing of the complexity and dynamic aspect. In our approach, the predictive maintenance schedule is thus considered as dynamic, which means different input parameters can be adjusted or changed for different maintenance schedule based on business needs. Different predicted RUL value of a machine component or all can be edited as an input for some business reasons e.g., different time windows may just need adjusted for fulfilling orders. The approach applies to the manufacturing factory itself as well as factories within the collaborative network. For a collaborative factory perspective, different adjustments i.e., maintenance schedule with different RULs of different pending failure period, maintenance associated with cost, resource availability, etc., can also be adapted for requirements such as urgent production deadline, resource constraints such as the availability of engineers, production plan, etc. This requires effective communication of the constraint information through the collaborative network.

Furthermore, in the Industry 4.0 network context, each participant firm has its specialized expertise and offers its service to the network. From a predictive maintenance service provider aspect, different machines need to be monitored in multiple organizations within a collaborative network factor. When scheduling a predictive maintenance plan, the predictive maintenance services can be planned as efficiently as possible, for example, the organizations geographical closed may schedule closer to save time, the similar machines in different organizations which similar conditions may change components at the same period to save costs, etc. Thus, this demands a predictive maintenance scheduling approach which considers complex systems for optimal maintenance schedule plan in collaborative manufacturing network with multiple manufacturing factories in a dynamic manner.

7.2 Predictive Maintenance Schedule for Industry 4.0 Multiple Machines and Components (PMS4MMC)

In this section, we first describe problem formulation for predictive maintenance scheduling in Section 7.2.1, and the formulation of the proposed PMS4MMC approach with mathematical model is provided in Section 7.2.2. We explain the overall predictive maintenance scheduling procedure applying PMS4MMC and predictive RUL Model of PMMI 4.0 (i.e., discussed in Chapter 6) as well as the detailed process of PMS4MMC is explained applying the key concepts identified in Section 7.2.3 and detailing the various processes i.e., algorithms utilized for PMS4MMC is discussed in Section 7.2.3.2.

7.2.1 Problem Formulation for Predictive Maintenance Scheduling

Determining a schedule of activities based on predictive failure detection of a machine/component is part of a predictive maintenance planning process (Mobley, 2002; Sang et al., 2021*b*). More precisely, it is the stage of maintenance schedule planning for future execution of the plan, incorporating different needs and constraints. Predictive maintenance scheduling involves the allocation of the available maintenance resources in Industry 4.0 manufacturing workflow. Determining a maintenance schedule demands a detailed description of the maintenance process including maintenance related information such as task, time, resources i.e., engineer, tools, spares, cost, etc. As it is clear, these decision problems have a strong combinatorial nature and consequently a high complexity, particularly in the context of complex Industry 4.0 environment.

Formally, a predictive maintenance scheduling problem is the allocation of a number N of predictive maintenance tasks, $N = 1, 2, ..., n$ on a set of pending failure machines or components, $M = 1, 2, ..., m$. Each task t consists of a type A_t of activities, where activity A_it of job t must be carried out on machine i. Each activity A_it has an associated processing time $P_it \in N$, an associated resource $R_it \in N$ and an associated cost $C_it \in N$ on machine i. Each task t will have associated an ordering R_t of the activities of A_t, reflecting the precedence ordering among activities. The goal of predictive maintenance scheduling is to find a maintenance schedule π of tasks over machines yielding an optimal value $f(\pi)$, where f denotes some objective function.

Predictive Maintenance Scheduling problems are dependent on information details of the factory setting (predictive failure of machine/component, availability of maintenance time windows, maintenance task, cost, production plan, etc.) (Mobley, 2002; Sang et al., 2021*b*). This indicates that different parameters (schedule dates, schedule times, schedule tasks, resources i.e., engineer, tools, spares, etc.) and different objective functions (optimal cost, optimal schedule time, etc.) require alternative statements of the general problem (Mobley, 2002; Sang et al., 2021*b*).

7.2.2 Formalization of PMS4MMC Maintenance Scheduling Optimization with Mathematical Model

The PMS4MMC maintenance scheduling optimization is formalized with a mathematical model, as part of optimal maintenance according to the following: for the replacement i.e., non-repairable and repairable machine/component, there is a trade-off between setup cost for the group of machine/component and remaining useful life (RUL) of the machine/component. So, cost will be charged for changing the machine/component before reaching to the end of its useful life. On the other hand, there is an opportunity for cost saving on running maintenance of the other machines/components in the same group. The number of maintenances for the same group will reduce the number of set-ups and associated cost.

For the repairable machine/components, the trade-off includes the cost of buying a new machine/component and the cost of repairing machine/component in its operating period. In general, the number of repairs will affect the next expected time to maintenance as the recurring maintenance will get shortened. And cost will incur to reproduce the same time of working for the maintenance. A dynamic maintenance repository (i.e., Figure 5.2 in chapter 5) must define for the repairing cost of each machine/component in each period.

For both replacement and repairable aspects, a penalty of downtime cost is charged if the maintenance period is scheduled more than their remaining useful life. This is because complex manufacturing systems operate in highly collaborative industries and downtime cost for the production line impact the whole collaborative chain. For instance, the machines/components are required after a prediction alert is detected. Due to ordering due dates, the factory operation continues without the required maintenance. By considering the risk of failure, if machine/component is used more than its predicted remaining useful life and by assigning down time cost, the proposed model can be assigned for the schedule period into RUL of each machine/component.

For maintenance information about items, cost, time and availability, predictive RUL (i.e., Chapter 6) and data model proposed in Figure 5.2 in Chapter 5 are utilized for information related repository. Using this, up-to-date information about maintenance items is updated, and available for processing the outstanding maintenance items.

The mathematical model and its indices, parameters and decision variables are presented in the following:

Indices

i number of each machine component $i \in 1, 2,... N$ *(N = total number of machine component)*

j index of the group number $j \in 1, 2, ... A$ *(A = total number of groups)*

t number of period $t \in 1, 2, ... A$ *(A = total number of periods)*

Parameters

CP_i Cost of replacement i

CR_i Cost of repairing$i$ *for the repairable machine/component*

RCi Cost of resources (i.e., engineer, tools) j *for the maintenance period*

$CGSU_j$ Cost of group set-up (operation of opening machine cost + down time cost) of part j *in its group*

CDT Cost of downtime of machine per period

RUL_i Remaining useful life of machine/component i *coming from machine learning prediction (unit in periods)*

G_{ij} A binary parameter for indicating if machine/component i *belongs to group* j *take the value of 1*

Decision Variables

MP_i Maintenance Period of machine component i

XP_{it} (0, 1) Maintenance scheduling of machine component i *in period* t

R_i (0, 1) (0, 1) If the machine component i *has to be repaired or not*

RN_i (0, 1) If the machine component i *has to be replaced or not*

D_{jt} (0, 1) If even one part from each group is scheduled to be maintained in period *t→1, otherwise→0*

K_{jt} (0, 1) (0, 1) Number of machine component from each group that is scheduled to be maintained in period *t*

$$Min \sum_{i=1}^{n} (((CP_i + CR_i) \times RN_i) + (RUL_i - MP_i)$$
$$+(CDT \times RC_j) + CGSU_j + \sum_{j=1}^{A} \sum_{t=1}^{T} (D_{jt} \times K_{jt})) \tag{7.1}$$

$$R_i + RN_i - 1 \qquad \forall i \tag{7.2}$$
$$MP_i \geq t - M \times (1 - XP_{it}) \qquad \forall i, t \tag{7.3}$$
$$MP_i \leq t + M \times (1 - XP_{it}) \qquad \forall i, t \tag{7.4}$$
$$\sum_{i-1}^{T} XP_{it} = R_i + RN_i \qquad \forall i \tag{7.5}$$
$$MP_i - RUL_i \in \{t\} \qquad \forall i \tag{7.6}$$
$$\sum_{i-1}^{N} XP_{it} \times G_{ij} \geq D_{jt} \qquad \forall t, j \tag{7.7}$$
$$\sum_{i-1}^{N} XP_{it} \times G_{ij} \leq M \times D_{jt} \qquad \forall t, j \tag{7.8}$$
$$\sum_{i-1}^{N} XP_{it} \times G_{ij} = K_{jt} \qquad \forall t, j \tag{7.9}$$
$$XP_{it},\ R_i,\ RN_i,\ D_{jt} \in \{0, 1\} \quad MP_i \geq 0 \qquad \forall i, t \tag{7.10}$$

The objective function is the minimization of: replacement or repairing cost, downtime cost when the machine component (factory operation) is stopped, maintenance/set-up cost over the maintenance period.

In the context of constraint, *7.2* states the machine/component must be repaired or replaced whereas maintenance period of each machine component is greater than current period in *7.3*. To identify maintenance period of each machine component based on its maintenance period, constraints *7.4* to *7.6* are defined by a binary variable. In the case of maintenance period with higher remaining useful life (i.e. the value of 0, otherwise 1), constraint *7.7* of a

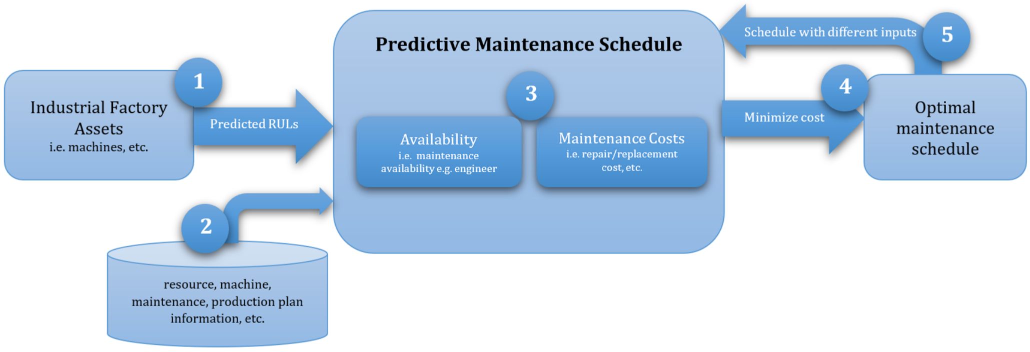


Fig. 7.2 Overall PMS4MMC Predictive Maintenance Schedule Procedure (Sang et al., 2021*a*)

binary variable is defined. To determine whether there is one machine/component of each maintenance group that is scheduled in period t (i.e., takes the binary value of 1, otherwise 0), constraint number *7.8* is described. The number of machine/components in each group that is scheduled in each period is defined by constraint *7.9*. And the conditions on the decision variables deal with constraint *7.10*.

7.2.3 PMS4MMC Predictive Maintenance Scheduling

In general, predictive maintenance scheduling is described as an optimization process which minimizes the overall cost supported by data-driven predictive RUL model and related data i.e. maintenance, to assign the resources over time regarding the maintenance activities as illustrated in the *Overall Predictive Maintenance Schedule Procedure* in Figure 7.2. The predictive maintenance scheduling involves predictive RULs, multiple factory machine components, the maintenance tasks, timestamps, and associated costs. The No. 1 input of Figure 7.2 represents the result of ‘data-driven maintenance’ listed in Section 7.1.1 (i.e., proposed predictive RUL Model of *PMMI 4.0* in chapter 5). The No. 2 input of Figure 7.2 indicates the rest of the list in Section 7.1.1. The ‘predictive maintenance schedule’, 3 in Figure 7.2 shows different schedule focuses such as maintenance availability and maintenance cost. It depends on which optimize factory(ies) is(are) selected by the user, for example, 4 in Figure 7.2 is selected as ‘minimize cost’. After ‘optimal maintenance schedule’, based on the input of ‘minimize cost’ i.e. No 5 in Figure 7.2, different predictive maintenance schedules will be provided.

Data-driven predictive maintenance schedule aims to provide the optimal output of conducting maintenance activities of the machines components with corresponding predicted RULs supported by manufacturing data such as maintenance, cost, task, resource. Essentially, the optimal output is achieved by minimizing the overall maintenance cost associated with the required maintenance activity, reducing downtime and cost. The duration i.e. short, medium, or long term of the predictive maintenance activity may become important, depending on the degree of the predictive maintenance activity, time, and cost. We first explain the integration of *PMS4MMC* and *PMMI 4.0* for *Predictive Maintenance Scheduling* in the next Section 7.2.3.1 and subsequently, the detailed process of *PMS4MMC Predictive Maintenance Schedule* of Figure 7.2 in Section 7.2.3.2.

7.2.3.1 Applying PMS4MMC and PMMI 4.0 for Predictive Maintenance Scheduling

The contribution of this work is to provide a predictive maintenance model which supports flexible integration of different components required for maintenance services in complex manufacturing environment. *PMMI 4.0* thus is proposed Chapter 5 for Industry 4.0 predictive maintenance solution that provides a coherent architecture of different key modules with related processes that can be flexibly integrated. To support complex Industry 4.0 systems, maintenance analysis in Figure 5.3 (also part of the maintenance decision support in Figure 5.4 in Chapter 5) can be done using *PMS4MMC* for maintenance scheduling based on the predictive RUL and maintenance related data as previously demonstrated in Section 7.2.3 for assisting maintenance decision making. Data from factory machine equipment tools, processes and systems should be collected and processed using big data and advanced analytics. The analytics including predictive maintenance services facilitate the factory staff e.g., operator for making effective maintenance related decision.

In the context of the proposed *PMMI 4.0* architecture platform in Figure 5.4 in Chapter 5, different FIWARE's adapters are deployed connecting and integrating the factory machine equipment tools and the Orion context broker. Sensor operation and condition are collected from these machine tools Data are then processed and stored in the platform databases using the data model as illustrated in Figure 7.2 in Section 7.2.3. Using machine data, predictive maintenance RUL model is built and deployed as FIWARE enabler, which can then be accessible to the users via NGSI API.

Using the data model in Figure 5.2 for better supporting maintenance, maintenance related data are stored in the maintenance repository in databases such as HDFS. The maintenance repository holds related maintenance data including existing and future maintenance schedule plan. Using the predictive maintenance RUL model, predicted RULs of potential failure of machines/components can be generated for predictive maintenance schedule planning. The predictive maintenance scheduling is facilitated by the different information related to maintenance, machine, or resource related data supported by the data model. The maintenance information are made available for the maintenance user assisting maintenance decisions.

At the maintenance decision support in *PMMI 4.0* in Figure 5.4 in Chapter 5, the maintenance analysis is initiated by the predicted RUL values or other potential failures of the factory machine equipment tools. The maintenance analysis is performed, allowing flexible inputs and producing a maintenance schedule plan as described in Figure 7.2 in Section 7.2.3. The output of the maintenance analysis leads to determining the maintenance schedule plan for all the task and related activities that take into consideration of different weights such as cost. In the analysis, the maintenance task would depend on the estimated automation or engineer task for the machine equipment tool which requires the corresponding maintenance activity. The time e.g. displacement, repair, the maintenance item or the automation of the repair machine equipment of the completed maintenance activity as well as the availability of the maintenance items for maintenance would also determine the aspect of the maintenance. For the availability, the availability of maintenance resources such as maintenance item and related replacement or repair are checked e.g., work in progress production and the corresponding qualified timeslot is considered. For the maintenance cost, the cost that is subject to conducting the maintenance activity for the required machines/components including the cost associated with downtimes, repair or replacement. The nature of the maintenance task and the maintenance engineer or team will also contribute to the cost. Essentially, the maintenance analysis is initiated and performed by the user e.g. maintenance engineer considering the described maintenance constraints including maintenance cost, maintenance resources and availability.

Maintenance analysis can also be initiated by the maintenance monitoring in *PMMI 4.0* in Figure 5.4 in Chapter 5. The maintenance monitoring can be configured for different notifications based on business or maintenance needs. Using the notification of the critical condition of each machine equipment tool including its future trend and RUL, the maintenance analysis is performed, analyzing the output of the predictive maintenance schedule optimization. Based on the analysis outcome, appropriate task and activity for an optimal maintenance schedule plan can be created. At this analysis, various critical maintenance asset condition and maintenance analysis based on time, cost, and availability are considered.

7.2.3.2 Detailed Process of PMS4MMC Predictive Maintenance Scheduling

In this section, applying the formalized *PMS4MMC* in Section 7.2.2 and considering the key factors described in Section 7.1.2, the following algorithms are established. *Algorithm 1* describes the overall *Predictive Maintenance Schedule Optimal Processing* which invokes related algorithms for executing the process. *Algorithm 2* describes the online maintenance monitoring i.e. maintenance monitoring in Section 5.2.3.2 in Chapter 5. *Algorithm 3* deals with retrieving the qualified maintenance items and *Algorithm 6* processes the aspect of the maintenance cost. *Algorithm 4* takes care of the maintenance time and availability for the required maintenance items whereas *Algorithm 5* processes the availability aspect.

We formulate the proposed *PMS4MMC* solution using the procedure (i.e., Figure 7.2) which utilizes the *Algorithms 1* - *Algorithm 5*. The process of *PMS4MMC* also addresses the key factors considered for predictive maintenance scheduling optimization for Industry 4.0 in Section 7.1.2 including *Multiple Maintenance Items Processing* i.e. Algorithm 3, *Maintenance Asset Processing* including maintenance time processing i.e. Algorithm 4, *Maintenance Availability Processing* i.e. Algorithm 5, *Maintenance Cost Processing* i.e. Algorithm 6, *Dynamic Predictive Maintenance Scheduling*, and the main *Predictive Maintenance Scheduling Optimal Processing* i.e. Algorithm 1 which deals with the whole process invoking the other algorithms.

The process of PMS4MMC can be explained by starting with *Predictive maintenance scheduling optimal processing* as depicted in *Algorithm 1*.

Algorithm 1 Predictive maintenance scheduling optimal processing

Input: maintenanceItemWithRUL, selectedMaintenanceItem
Output: maintenance schedule
Initialization: Initialize the maintenance schedule to null.
Get assets with RUL: maintenanceAssets = Get Maintenance Assets(maintenanceItemWithRUL)
Get assets with selected machines: maintenanceAssets = Get Maintenance Assets(selectedMaintenanceItem) ▷ user input or alert monitoring
Get time windows for maintenance items: maintenanceAssets = Get Time Windows for maintenanceAssets
Display maintenance items: Show List of maintenance items
Determine maintenance for maintenance items: User determines maintenance tasks for maintenance items
Get the input(s) of the selected future time windows: time windows of maintenanceAssets = List of maintenance time windows
Getting resources with desired maintenance time windows, tasks: time windows of maintenanceAssets = List of maintenance time windows
Determine availability of resources for the maintenance: time windows of maintenanceAssets = List of maintenance time windows
Getting maintenance cost: time windows of maintenanceAssets ▷ get maintenance cost based on time and availability from resource repository, invoke algorithm Maintenance Cost Processing()
Compute optimal maintenance:

for $i \in$ maintenanceAssets **do**
    textsfif item is the same window period, then apply maintenance group, availability, time, cost
        i of maintenanceGroup += maintenanceAssets
        i of availability += maintenanceGroupAvailability
        i of time = maintenanceGroupTime
        i of cost = maintenanceGroupCost
end for

$$OptimizedSchedule = \sum_{i-1}^{N_{maintenanceAssets}} (maintenanceGroup_i, cost_i, time_i, availability_i)$$

return maintenance schedule = OptimizedSchedule

First, machine sensor data i.e., operation, condition, etc. must be processed for the Predictive RUL Model as described in Section 7.2.3 (i.e., detailed the proposed predictive model in Chapter 6). The RUL Model is run against potential maintenance machine components. This produces a list of maintenance items with RULs which can be described as pending maintenance items due for a future time window e.g., 5 days based on the RUL values (an example of this can be found at Table 7.2 describes 5 machine components with different RUL values over 5 days' time window which can then be used as the parameter inputs for maintenance scheduling). This then initiates the predictive maintenance schedule as described in *Algorithm 1*.

Alternatively, potential maintenance can be inputted from *user input* of machines listing or *online(real-time) notification* which is set up for alerting key machine items as real-time monitoring, part of the maintenance decision support in the *PMMI 4.0* platform as described in Chapter 5.

In the case of user selection, a user can select different machines based on requirements such as pending maintenance, etc., from the machine lists which can be provided by the machine repository. Both maintenance items with RUL and user selected items can then be combined for the consideration of maintenance planning.

For *online(real-time) notification* (i.e., alert monitoring, part of the maintenance decision support in the PMMI 4.0 platform in Chapter 5) as described in *Algorithm 2*, several underlying factory machines *N* are considered. Real-time data from these machines are collected and processed for maintenance monitoring and alert notification. The collected data derive the key state of each maintenance machine item. Threshold values are determined for each maintenance item based on the characteristic of the machine equipment. The alert level of *N* represents the threshold value of the state of each maintenance item. Each item alert *N* represents the alert indicator(normal, abnormal) for monitoring processing and alert notification which is triggered by processing the key state and the threshold value. Certain maintenance tasks such as minor adjustments are considered for automation. In this instance, the executable maintenance task will be processed when the alert triggers the threshold, and the alert is either above the alert level or the indicator is abnormal. After the task is completed, the corresponding alert item *N* is set to normal. An engineer or operator will be attended when the problem i.e. the maintenance task cannot be resolved and the corresponding alert item *N* will then be updated as normal.

In *PMMI 4.0*, based on business needs, different FIWARE's components can be integrated for for maintenance monitoring and alert notification. Maintenance alert levels e.g. detection of different thresholds such as failure, low-level temperature or oil can be configured as part of FIWARE's complex event processing for real-time analytics. The event process is facilitated by Cosmos Spark stream processing and the Orion context broker. Based on the nature of the alert notification, maintenance operator or engineer can perform the appropriate actions, as part of the maintenance scheduling plan in the maintenance analysis as described in Figure 7.2 (i.e., No. 3) of the *Overall PMS4MMC Predictive Maintenance Schedule Procedure*.

Algorithm 2 Online (real-time) maintenance processing

```
for i ∈ maintenanceItems do                              ▷ each key maintenance item
    if currentState(i) < alertLevel(i) then
        break                                            ▷ No outstanding alert item
    end if
    alert(i) = true
    for t ∈ i do
        if task(t) == true then
            do task (j)          ▷ maintenance task operation (automation)
            waitForTaskExecution()
        end if
        if currentState (i) < alertLevel (i) then
            set currentState (i) = false                 ▷ set as completed
        else
            for o ∈ operator(i) do
                if operator o == true then
                    do task (o)                          ▷ maintenance operation
                    set task (o) = false
                    set alertLevel (i) = false
                end if
            end for
        end if
        if alertLevel(i) == false then

▷ No outstanding alert item
        end if
    end for
end for
```

In getting multiple maintenance items, the input parameter of maintenance items including maintenance items with RUL, user selected inputs as well as online(real-time) alert notification, are being processed to retrieve any corresponding pending machine or component items invoking the *Algorithm 3*. This is facilitated by the machine repository who stores information about factory equipment tools i.e., multiple machine components, as part of Figure 7.2 (i.e. No. 2).

Algorithm 3 Get Maintenance Assets

```
Input: maintenanceItemWithRUL, selectedMaintenanceItem
Output: maintenance assets
Initialization: Initialize maintenance assets to null.
Get machine equipment items:        ▷ retrieve from machine repository in a database
    maintenance assets = execute get machine equipment items
    maintenance assets += maintenanceItemWithRUL
Process outstanding items:
for i ∈ maintenance assets do                    ▷ each maintenance item i
    if i is multiple machine or component then
        for m ∈ i do
            if m requres maintenance then
                maintenance assets += m
            else
                break
            end if
        end for
    else if i is single machine or component then
        if m requres maintenance then
            maintenance assets += m
        else
            break
        end if
    end if
end for
return maintenance assets
```

Algorithm 3 processes retrieving items which required maintenance, considering multiple machines components. In the context of multiple machines components, only maintenance required items are considered by processing through its related machine components. The whole process is facilitated by the machine repository which provides information for getting the outstanding items for maintenance activity within similar time window period.

Regarding the *maintenance time window* in *Algorithm 1*, the range of current available maintenance time windows is provided for the maintenance engineer or user using a repository in a database which holds future available maintenance time which are reconciled with the current production plan. The maintenance time window in the repository is updated when any production plan or different maintenance is changed, so that the maintenance engineer can get the latest range of available maintenance time.

With the outstanding maintenance items and available maintenance windows, the maintenance tasks such as repair, placement, etc. should be determined by the maintenance engineer. Different information such as historical diagnostic maintenance information, usage, machine base data, etc., should be available for the decision maker at the maintenance support analysis as described in PMMI 4.0 architecture in Figure 5.4 Chapter 5.

Then, the No 3 in Figure 7.2 processes by invoking different algorithms for the required maintenance. Initially, based on the nature of the pending predictive failure, the maintenance activity is decided. This process may consider activities such as replacement or repairing (minor or major) existing machine equipment. In the case of dependency, conducting a maintenance activity may be increased by the required task accommodating the dependent machine component, e.g., stopping and restarting the entire system. Other consideration may include whether the maintenance item meets any existing policy such as age which is available (i.e., maintenance repository) at the maintenance analysis in Figure 5.3.

When the qualified items with the corresponding maintenance activity i.e. repair/replacement are decided, then the maintenance time i.e. *Algorithm 4* is invoked. *Algorithm 4* deals with determining the time for the maintenance activity, considering multiple machines components.

Algorithm 4 Maintenance time processing

```
Input: maintenanceItems
Output: maintenance time
Initialization: Initialize maintenance time to zero.
if maintenanceItems is emptyset then        ▷ check if maintenance items is provided or not
    return no item needs to be maintained
end if
for i ∈ maintenanceItems do        ▷ each maintenance item i
    if i is repair, or major replacement, or replacement then
        maintenance time of i = repair, or major repair, or replacement time
    end if
    if i is any defined policies then    ▷ item meets any defined maintenance policy such as age, etc.
        maintenance time of i = major repair or replacement time
    end if
    if i required additional time then
        additionalTime = get additional time (i)    ▷ additional time for the maintenance such as downtime from stopping, restarting, etc. and to add on as progress is made from resource repository
        maintenance time of i += additionalTime
    end if
end for
return maintenance time
```

The process takes inputs as the outstanding maintenance items which are available for the maintenance engineer/user at the maintenance analysis as described in Figure 5.3. The maintenance time is determined by considering the maintenance activity time for each item from the resource repository which stores maintenance task i.e., repair or replacement with associated maintenance time e.g. 1 day, etc. Also, the consideration may be whether maintenance item meets any defined maintenance policy such as age, etc. For the overall downtime, various aspects such as the time for start-up and shutdown of the machine, the time for an engineer or operator to conduct the maintenance activity, the maintenance time for each machine component repair, replacement, readjustment, or displacement, etc. are considered. The state of the maintenance activities such as failure, worn, may add further maintenance time. The sum of these variables can be considered as the overall downtime of a product line, affecting the whole manufacturing chain.

Based on the maintenance activity and time for the required maintenance items, the resource required is determined using resource repository. Resource such as engineer, spare parts, replacement items based on the nature of predicted failures are considered, and the required engineer/spare parts are to be assigned.

Then, *Algorithm 5* is invoked for processing the *availability of the maintenance* items with associated resources i.e. engineer, tools, considering multiple machines components. The availability refers to the status i.e. available for a maintenance operation, of the machine equipment with associated components i.e. spare parts or replacement item, processes i.e. checking against production plan, as well as maintenance engineer/operator, required tools, etc. Getting part of the availability information, other activities, processes, etc., is coordinated for achieving an optimal maintenance activity with minimal impact.

Resource such as engineer, tools can also be assigned by the nature of pending failure, for example the pending maintenance is potentially urgent for maintenance, then the maintenance decision maker can assign the engineer with required tools appropriately, possibly higher priority over the maintenance period of the available time windows regardless cost. If maintenance decision maker is not required, then the optimal resource regarding maintenance time, cost, availability is assigned depending on the nature of pending failure.

Algorithm 5 Maintenance availability processing

```
Input: maintenanceItems, maintenanceTime
Output: maintenance availability
Initialization: Initialize maintenance availability to emptyset.

if maintenanceItems is emptyset then    ▷ check if maintenance items is provided or not
    return return no maintenance items
end if

if maintenanceTime is emptyset then    ▷ check if maintenanceTime is provided or not
    return return no maintenance time
end if

for i ∈ maintenanceItems do    ▷ each maintenance item i
    if t is emptyset then
        break    ▷ go to next maintenance item
    end if
    resource = get resource from repository (maintenanceItems, maintenanceTime)    ▷ retrieve required resource i.e. engineer tools for items with maintenance time from resource repository
    for r ∈ resource do    ▷ each resource t
        if r resource is available for maintenance item i which requires priority i at maintenance time of maintenance time then
            maintenance availability = r resource    ▷ assign resource i.e. engineer tools
        else if r resource is available for maintenance item i which do require priority i at maintenance time of maintenance time then
            maintenance availability = User Input for resource with priority    ▷ resource i.e. engineer tools from user input for desired resource priority
        else if r of resource is not available for maintenance at maintenance time of maintenance time then
            maintenance availability = User Input for resource    ▷ resource i.e. engineer tools from user input for desired maintenance time
        end if
    end for
end for
return maintenance availability
```

Based on the qualified maintenance items and their availability, the available time slots are then processed using the resource repository. Using the RUL time window of the input items and their corresponding availability, available maintenance slots are determined.

Then, the cost of the maintenance activity can be determined. *Algorithm 6* illustrates the process for *maintenance cost processing* which considers multiple machines components. The qualified maintenance items with their corresponding time and cost are considered as the input parameters. In this process, flexible or dynamic costs that incur for maintenance activity is supported by accepting an input parameter as fixed cost for the item.

Algorithm 6 Maintenance cost processing

```
Input: maintenanceItems, availability, time, cost ▷ cost input is for any dynamic cost incurred for maintenance
Output: maintenance cost
Initialization: Initialize maintenance cost to zero.
if maintenanceItems is emptyset then ▷ check if maintenance items is provided or not
    return Return no maintenance items
end if
if availability is emptyset then ▷ check if availability is provided or not
    return Return no availability
end if
if time is emptyset then ▷ check if time is provided or not
    return Return no maintenance cost
end if
for i ∈ maintenanceItems do ▷ each maintenance item i
    projectedMaintenanceCosts = get maintenance cost (i, t of time, a of availability) ▷ get list of cost incurred for maintenance i.e. repair, replacement, resource i.e, engineer, tools, etc. from resource repository and maintenance time period
    if i is applicable for possibleMaintenanceCosts and not applicable for input cost then ▷ check if maintenance items is incurred for cost
        if i is applicable for Priority then ▷ check if maintenace is urgent i.e. repair/replacement is needed as soon as possible,
            maintenanceItemCost = get earliest time windows cost ▷ get cost of the earliest time windows from projectedMaintenanceCosts
        end if
        if i is not applicable for Priority then ▷ check if maintenace is urgent State maintenanceItemCost = optimal cost of projectedMaintenanceCosts ▷ no urgent maintenance required, then cheapest/optimal cost
        end if
        if i is applicable for overhead then ▷ any overhead cost, to add on as progress is made i.e. overall labour, cost incurred for downtime, etc. from resource repository
            overheadCost = overhead cost of maintenance
        end if
        if i is applicable for input cost then ▷ check if dynamic/fixed input cost applied or not i.e. fixedcost incurred from resource repository
            maintenance cost += cost + overheadCost
        else
            maintenance cost += maintenanceItemCost + overheadCost
        end if
    end if
end for
```

The *maintenance cost* is based on a number of variables required for conducting the maintenance activity. These variables include individual maintenance time and cost for performing the required activity. Additional variables considered for cost processing include overhead cost such as cost of engineer, setup or dynamic cost. The resource repository is used for determining maintenance related information.

Essentially, minimizing the overall cost related to conducting the maintenance activity and reducing downtime is the objective. To achieve this, the concept of maintenance group is applied (Dekker et al., 1997*b*). In this way, the overall maintenance activity for the required maintenance items and associated activities including setup cost, stopping and restarting factory floor, a maintenance visit for several activities at one interval, rather than for multiple instances, are considered.

PMS4MMC process is then run to get an optimal maintenance schedule, and to solve the proposed mathematical model with its input data, *Python Pulp Optimization* is used. Using real world cases and parameters (i.e., application cases in Chapter 3) in our problem, the RUL values of the machines/components are based on the predicted value derived from real condition of machine through sensor data as proposed in Chapter 6. Then, by solving optimization model, an output for the maintenance scheduling of the machine components can be used by the decision maker in their maintenance schedule planning.

To support the dynamic nature of Industry 4.0 manufacturing network i.e. different business requirements or changes, etc., the PMS4MMC supports the aspect of *Dynamic Predictive Maintenance Scheduling* by allowing the handling of new data i.e. machine, maintenance, etc. as illustrated in No 5 of Figure 7.2. Using the predictive maintenance schedule of Algorithm 1 and related processes No1 – No4 of Figure 7.2 with the corresponding *Algorithms 2- 6*, a desired plan can be created by using updated/new RUL values, maintenance data and adjusting appropriate optimization parameters. Upon receiving new sensor data, the predictive RUL model can be run again and an optimized RUL model can also be re-tuned/deployed and an optimized maintenance schedule can be produced as illustrated in No 5 of Figure 7.2. The next section provides the implementation of the solution using the FIRST project industrial cases and different scenarios, and the corresponding results are discussed.

7.3 Experiment Study, Evaluation and Analysis

To demonstrate our proposed solution, the scenarios and data used must reflect the nature and requirements of Industry 4.0 i.e. multiple machine components (i.e. Section 7.1.2). The datasets including different machine components with related data (i.e. Table 7.1,

Table 7.2, Table 7.3, Table 7.4 in Section 7.3.1 are used. To validate the dynamic nature of Industry 4.0 and business needs, different scenarios with the consideration of multiple machine components and associated costs are established based on the maintenance data from the FIRST industrial case.

As such, this section presents the verification of *PMMI 4.0* and *PMS4MMC* using the FIRST industrial dataset. In section 7.3.1, we present the FIRST manufacturing case and associated maintenance data. The different scenario cases, corresponding results i.e. Figure 7.3, Figure 7.4, Figure 7.5 , Figure 7.6 and Figure 7.14 and a summary of the scenario cases i.e. Table 7.5 are presented in Section 7.3.1. In addition to the manufacturing case, a virtual factory case is applied using *PMS4MMC* in Section 7.3.2.

To evaluate the proposed *PMS4MMC* algorithms and scheduling optimizations, the performance of the algorithms and scheduling optimization are discussed in and the overall performance of the algorithms for *PMS4MMC* is presented in Section 7.3.3. The impact of maintenance scheduling optimization and the performance comparison with optimization packages for optimal cost and downtime over the different cases are presented in Section 7.3.3.

7.3.1 Applying PMMI 4.0 and PMS4MMC with FIRST Manufacturing Case

For *Maintenance Analysis*, we considered one group of CNC machines (with 21 components) from the product line of the FIRST manufacturing application case described in Chapter 3. The considered case contains information such as resource index (i.e., resource such as engineer), predicted RULs, maintenance tasks, timestamps, and related costs. The sample features used in this work is presented in Table 7.1. In *PMMI 4.0* context, these maintenances related information (i.e. Section 7.2.3, Section 7.2.3.1) are being updated and stored using databases i.e. HDFS, etc., and are accessed via API, as illustrated in No 2 of Figure 7.2.

Using the maintenance data, RUL values over a time window of 5 days period are identified as illustrated in Table 7.2. From Table 7.3 and Table 7.4, RUL for *comp 3, comp 8, comp 15, comp 17, comp 18 of one CNC machine and m1_comp 3, m1_comp 8, m1_comp 15, m1_comp 17, m1_comp 18, m2_comp 3, m2_comp 8, m2_comp 15, m2_comp 17, m2_comp 18* of two CNC machines, and *m1_comp 3, m1_comp 8, m2_comp 7, m2_comp 8, m3_comp 10, m4_comp* 5 of four CNC machines are within *15, 16, 18, and 20* remaining useful life (days) over a time window of 5 days period. Using these RUL information, the decision maker e.g. an engineer or operator can initiate the analysis. Access to maintenance information is made via API (i.e. No 2 of Figure 7.2).

Table 7.1 Sample data for predictive maintenance schedule

Item	Description	Data Type
Index	The index number of each record	int
Resource Index	The resource index number which represents factory resources such as engineer, setup, dependency	int
Machine/Component Id	The Identification number of each machine component	int
Maintenance	The description of maintenance i.e. repair, replacement	int
Date Time	The timestamp of the maintenance to be performed.	timestamp
Cost	The cost of the maintenance activity i.e. individual item, setup, engineer, etc.	float

Table 7.2 RULs for a CNC machine with multiple components

RUL	comp3	comp8	comp15	comp17	comp18
15			*M*		
16				*M*	
18	*M*				*MRp*
20		*M*			

RUL = predicted value in day
Comp *n* = machine component
M = maintenance repair
MRp = maintenance renew or replacement

Table 7.3 RULs for two CNC machines with multiple components

RUL	m1_comp3	m1_comp8	m1_comp15	m1_comp17	m1_comp18	m2_comp3	m2_comp8	m2_comp15	m2_comp17	m2_comp18
15			*M*					*M*		
16				*M*					*M*	
18	*M*				*MRp*	*M*				*MRp*
20		*M*					*M*			

RUL = predicted value in day
m *n*_comp *n* = machines components
M = maintenance repair
MRp = maintenance renew or replacement

Table 7.4 RULs for four CNC machines with multiple components

RUL	m1_comp3	m1_comp8	m2_comp3	m2_comp18	m3_comp10	m4_comp5
15						
16			*M*			
18	*M*			*MRp*	*M*	
20		*M*				*M*

RUL = predicted value in day
m *n*_comp *n* = machines components
M = maintenance repair
MRp = maintenance renew or replacement

For the overall predictive maintenance activities, it takes inputs as the predicted items (i.e. *Comp3, Comp 8, Comp 15, Comp17, and Comp 18* of one CNC machine or *m1_comp 3, m1_comp 8, m1_comp 15, m1_comp 17, m1_comp 18, m2_comp 3, m2_comp 8, m2_comp 15, m2_comp 17, m2_comp 18* of two CNC machines of two CNC machines, or *m1_comp 3, m1_comp 8, m2_comp 7, m2_comp 8, m3_comp 10, m4_comp 5* of four CNC machines) with associated costs, resources (i.e. engineer) and the availability of the resources over five different periods (i.e. five days period) with two different options (i.e. during/after business hour). Repairs and replacement are considered for maintenance as illustrated in Table 7.2, Table 7.3 and Table 7.4. The maintenance activity i.e. repair, or replacement can also be decided by a maintenance engineer based on the predicted RUL information and other related maintenance information e.g. the availability of engineer, etc.

Based upon the constraints described in Section 7.2.2, the predictive maintenance schedule is planned for all the machine components over the RUL period, minimizing the overall maintenance cost and reducing downtime. The costs are extracted from the case data for this model. Since the cost of RUL is relatively less, the RUL values derived from the machine components are mostly utilized for the predictive maintenance scheduling. A time window of 5 days period with 2 time slots per day, optimizations such as engineer, availability of resource and maintenance items based on the resource i.e. factory location/dependency are applied to reduce the high value of setup/location cost. This leads minimizing the number of set-ups with associated other costs including resource-based maintenance.

The experiment case scenarios are based on a combination of inputs i.e. different maintenance operation hours, cost, task, etc., and their corresponding results are presented. A range of case can be formed due to the complexity of Industry 4.0 systems i.e. multiple machines/components (i.e. Section 7.1.2). To better reflect this, we define the scope of the case scenario used into multiple components of one machine and multiple components with multiple machines in the context of FIRST manufacturing setting. For the consideration of the input selection, since downtime and cost are high important to the manufacturing chain (Deloitte, n.d.; Mobley, 2002; Sang et al., 2021*a*), two different input cases are selected for the four scenario cases. In the scenario cases in Section 7.3.1.1, the predictive maintenance schedule is planned without the constraint of 'the maintenance needs to be performed after business hour', therefore, the scheduling could cost a reasonable lower price. On the other hand, the scenario case in Section 7.3.1.2, 'business hour' is included for planning the predictive maintenance schedule, which results in notable higher costs. The overall costs include the cost for engineer, maintenance task i.e. repair/replacement and setup i.e. downtime of factory operation. The scenario cases are applied with the defined scope (i.e. multiple components of one machine and multiple components with multiple machines), available resource i.e., engineer, tools, and setup for all the experiments.

To better evaluate our solution, we have done further experiment using additional scenario cases i.e. multiple machines components with a combination of inputs using FIRST manufacturing case. A summary of the compiled results is presented in Section 7.3.1.11. In addition to the manufacturing case, our solution is verified using FIRST Virtual Factory case (i.e. Section 3.2 in Chapter 3), and the corresponding case and results are presented in Section 7.3.2.2.

The procedure of *Predictive Maintenance Schedule* and the *algorithms* of maintenance optimization in Section 7.2 are applied for all experiments.

7.3.1.1 Experiment scenario case 1 - multiple components with minimal impact on business hour operation scheduling

The experiment scenario case represents the scenario with Multiple Components with Minimal Impact on Business Hour Operation Scheduling Case (MCMIBHOSC). At the *Maintenance Analysis* for the CNC with multiple components case in Section 7.3.1 (i.e. comp 3, comp 8, comp 15, comp 17, comp 18 of one CNC machine in Table 7.2), the decision maker makes various input choices for MCMIBHOSC predictive maintenance schedule plan as illustrated in Figure 7.3 (a). These choices include the cost for maintenance task i.e. repair/replacement, setup cost i.e. shutdown/up factory machine, each item cost of the time slot as well as the associated resource costs such as engineer, tools.

The subfigure (a) of Figure 7.3 depicts the overall maintenance costs including resources of engineer, setup, tools based on inputs i.e. all maintenance items for the 5 maintenance components over the 5 days period.

Based on the input choices, subfigures (b), (c), (d) and (e) are produced as the results in Figure 7.3. Different available schedule slots with different cost options over 5 days period

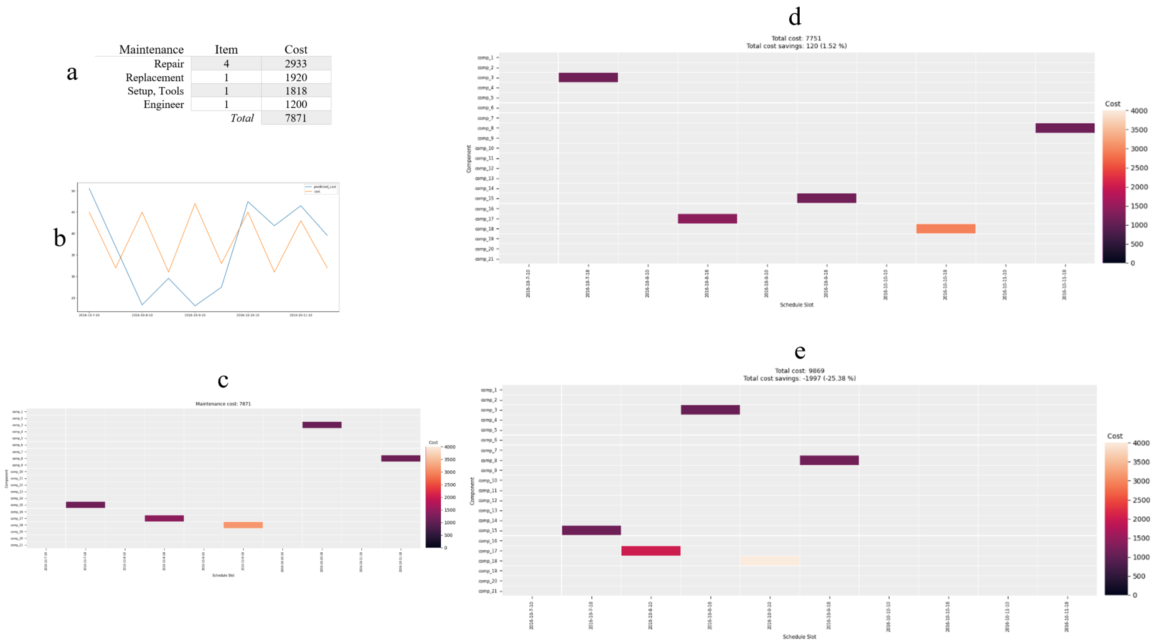


Fig. 7.3 Results of case 1 (Sang et al., 2021*a*)

are represented by the x-axis of the subfigures (c), (d) and (e) and the corresponding y-axis represent the multiple machine components for the maintenance scenario case.

Subfigure (b) depicts an overall predicted cost comparison between the optimized cost of subfigure (e) (i.e. blue) and actual cost of subfigure (c) (i.e. yellow) over the same period. Subfigure (c) shows maintenance schedule with group maintenance over 5 days period without optimization whereas the optimization options are presented in subfigure (d) with over 1% cost saving with different slots with an optimal downtime with more cost 25% in subfigure (e), compared with actual cost in subfigure (c) with different slots.

7.3.1.2 Experiment scenario case 2 - multiple components including business hour operation scheduling

In this case, it represents the scenario for *Multiple Components including Business Hour Operation Scheduling Case (MCBHOSC)*. Similarly, for the CNC with multiple components case in Section 7.3.1 (i.e. comp 3, comp 8, comp 15, comp 17, comp 18 of one CNC machine in Table 7.2), the decision maker makes similar input choices including after business hour for MCBHOSC predictive maintenance schedule plan. These choices for the case include the cost for maintenance task i.e. repair/replacement, setup cost i.e. shutdown/up factory machine, each item cost of the time slot as well as the associated resource costs such as engineer, tools as illustrated in Figure 7.4 (a).

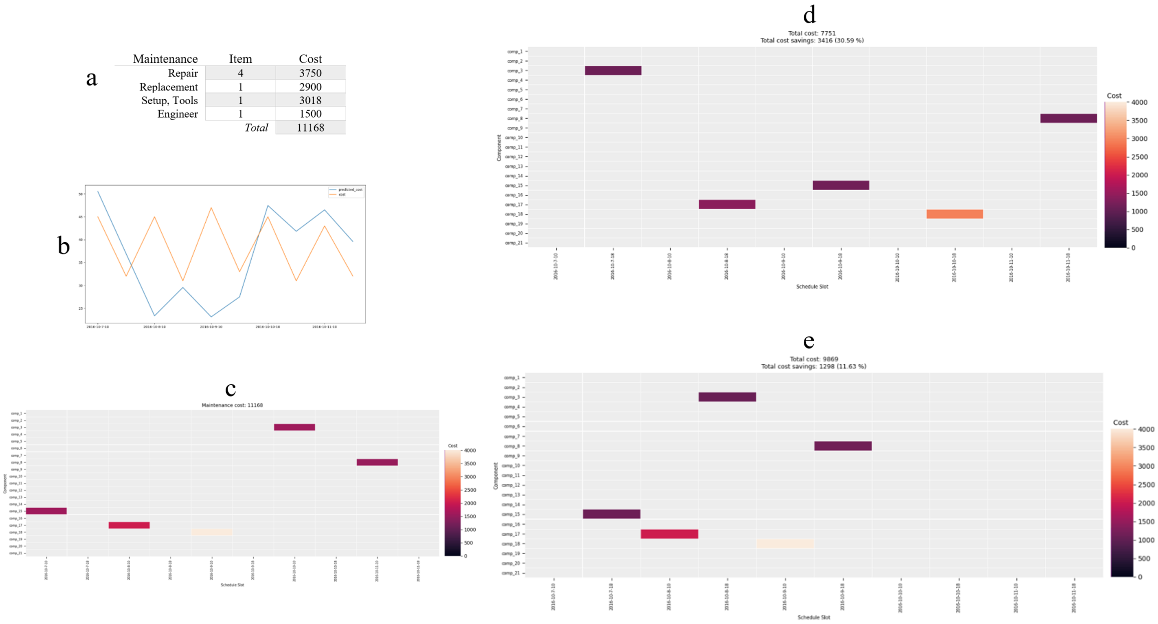


Fig. 7.4 Results of case 2 (Sang et al., 2021*a*)

Based on the input choices, results of subfigures (b), (c), (d) and (e) are produced as shown in Figure 7.4. Subfigure (b) depicts the overall predicted cost comparison between the optimized cost (i.e. subfigure d) and actual cost (i.e. subfigure c) over the same period. Subfigure (c) shows maintenance schedule over the 5 days period without optimization, whereas the optimization options can be achieved over 30% cost saving with different slots in subfigure (d) and over 11% cost saving in subfigure (e) respectively.

7.3.1.3 Experiment scenario case 3 - two machines with multiple components without minimal impact on business hour operation scheduling

In this scenario, the case represents for *Multiple Machines Components (2 Machines with multiple components) without Minimal Impact on Business Hour Operation Scheduling Case (2MMCMIBHOSC)*.

At the Maintenance Analysis for the CNC machines with multiple components case in Section 7.3.1 (i.e. *m1_comp 3, m1_comp 8, m1_comp 15, m1_comp 17, m1_comp 18, m2_comp 3, m2_comp 8, m2_comp 15, m2_comp 17, m2_comp 18* of two CNC machines in Table 7.3), the decision maker makes input choices for 2MMCMIBHOSC predictive maintenance schedule plan. These choices for the case include the cost for maintenance task i.e. repair/replacement, setup cost i.e. shutdown/up factory machine, each item cost of the time slot as well as the associated resource costs such as engineer, tools as illustrated in Figure 7.5 (a).

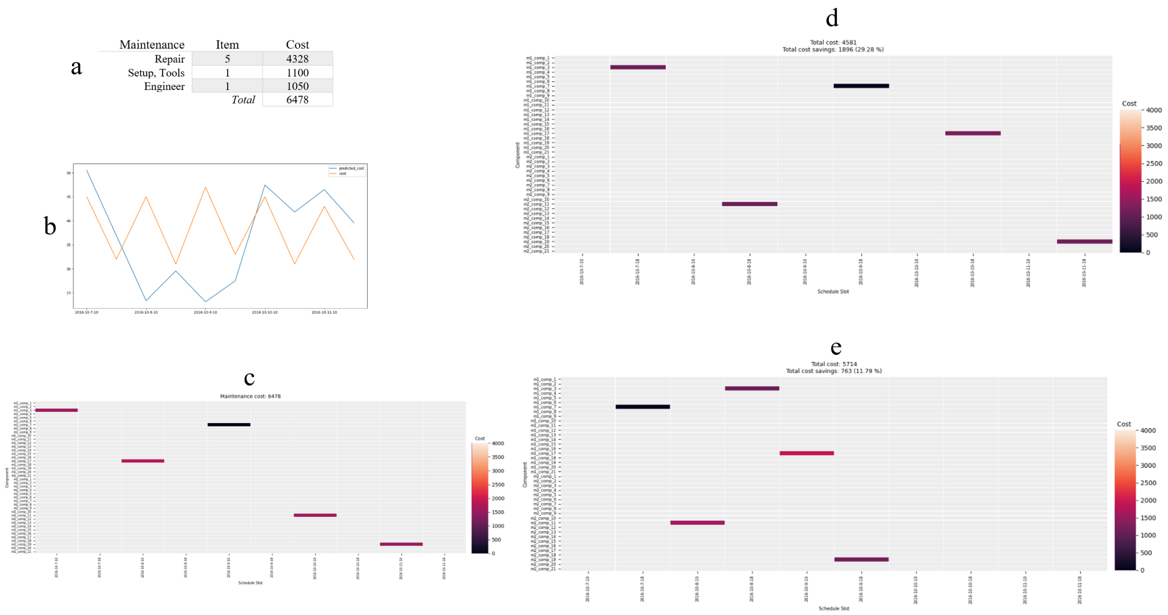


Fig. 7.5 Results of case 3

Based on the input choices, the results are presented in Figure 7.5. Subfigure (b) depicts the overall predicted cost comparison between the optimized cost (i.e. subfigure d) and actual cost (i.e. subfigure c) over the same period. Subfigure (c) shows maintenance schedule over the 5 days period without optimization, whereas the optimization options can be achieved over 29% cost saving in subfigure (d) and over 11% cost saving in subfigure (e) with different slots respectively.

7.3.1.4 Experiment scenario case 4 - four machines with multiple components with/out minimal impact on business hour operation scheduling

In this instance, the case illustrates the scenario for *Multiple Machines Components (4 Machines with multiple components) with/out Minimal Impact on Business Hour Operation Scheduling Case (4MMCMIBHOSC)*.

Similarly, for the CNC machines with multiple components case in Section 7.3.1 (i.e. *m1_comp 3, m1_comp 8, m2_comp 7, m2_comp 8, m3_comp 10, m4_comp 5* of four CNC machines in Table 7.4), the decision maker makes input choices for 4MMCMIBHOSC predictive maintenance schedule plan. These choices for the case include the cost for maintenance task i.e. repair/replacement, setup cost i.e. shutdown/up factory machine, each item cost of the time slot as well as the associated resource costs such as engineer, tools as illustrated in Figure 7.6 (a) for 4MMCMIBHOSC scenario case.

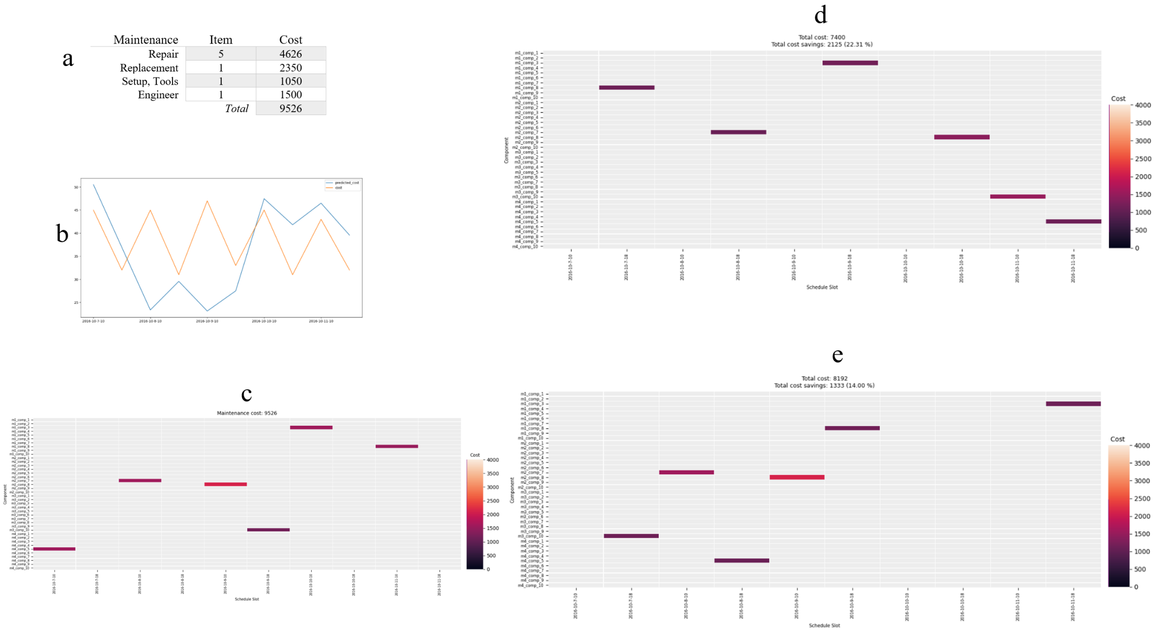


Fig. 7.6 Results of case 4

Based on the input choices, the results are presented in Figure 7.6. Subfigure (b) depicts the overall predicted cost comparison between the optimized cost (i.e. subfigure d) and actual cost (i.e. subfigure c) over the same period. Subfigure (c) shows maintenance schedule over the 5 days period without optimization, whereas the optimization options can be achieved over 22% cost saving in subfigure (d) and over 14% cost saving in subfigure (e) with different slots respectively.

In addition to the described four experiment scenario cases, we present the following additional scenario cases i.e. multiple machines/components with a combination of inputs using the FIRST manufacturing case.

7.3.1.5 Case 5 - three machines with multiple components during business hour operation scheduling

Using the CNC machines with multiple components case in Section 7.3.1, different input choices are considered for the scenario case. This includes three machines with multiple components, maintenance activity during business hour, cost for engineer, setup, individual repair/replacement and associated timeslot as illustrated in Figure 7.7 (a).

Based on the input choices, the results are presented in Figure 7.7. Subfigure (b) depicts the overall predicted cost comparison between the optimized cost (i.e. subfigure d) and actual cost (i.e. subfigure c) over the same period. Subfigure (c) shows maintenance schedule over

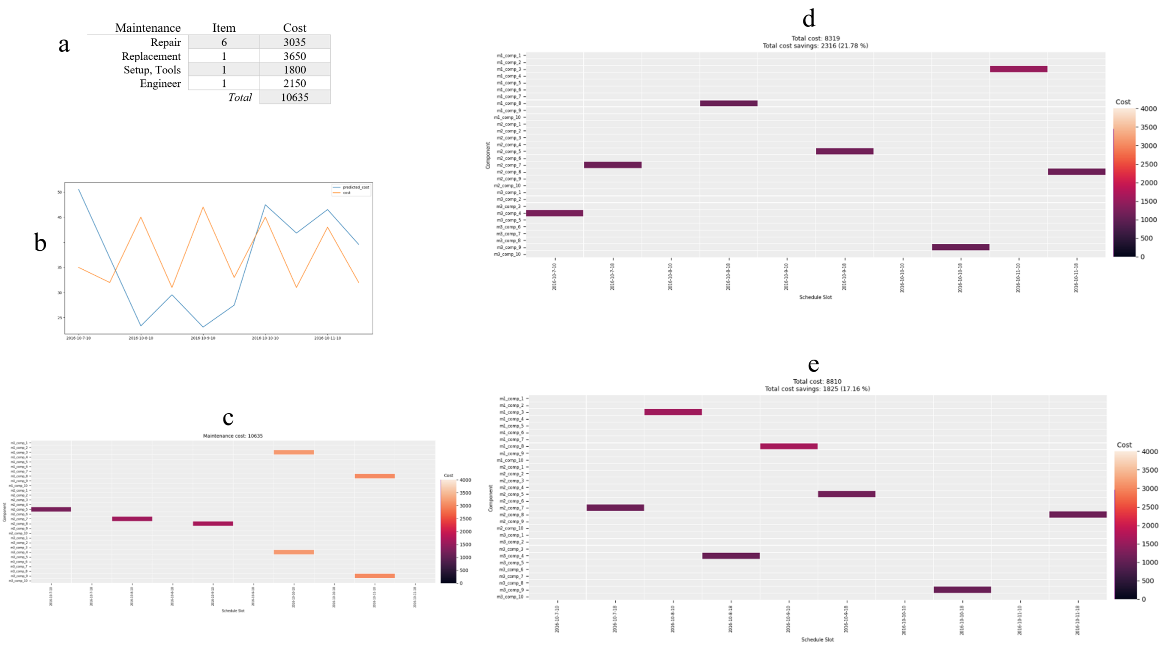


Fig. 7.7 Results of case 5

the 5 days period without optimization, whereas the optimization options can be achieved over 21% cost saving in subfigure (d) and over 17% cost saving in subfigure (e) with different slots over the same parameters and period respectively.

7.3.1.6 Case 6 - three machines with multiple components minimal impact business hour operation scheduling

Using the CNC machines with multiple components case in Section 7.3.1, different input choices are considered for the scenario case. This includes three machines with multiple components, maintenance activity after business hour, cost for engineer, setup, individual repair/replacement and associated timeslot as illustrated in Figure 7.8 (a).

Based on the input choices, the results are presented in Figure 7.8. Subfigure (b) depicts the overall predicted cost comparison between the optimized cost (i.e. subfigure d) and actual cost (i.e. subfigure c) over the same period. Subfigure (c) shows maintenance schedule over the 5 days period without optimization, whereas the optimization options can be achieved over 6% cost saving in subfigure (d) and over 13% cost saving in subfigure (e) with different slots over the same parameters and period respectively.

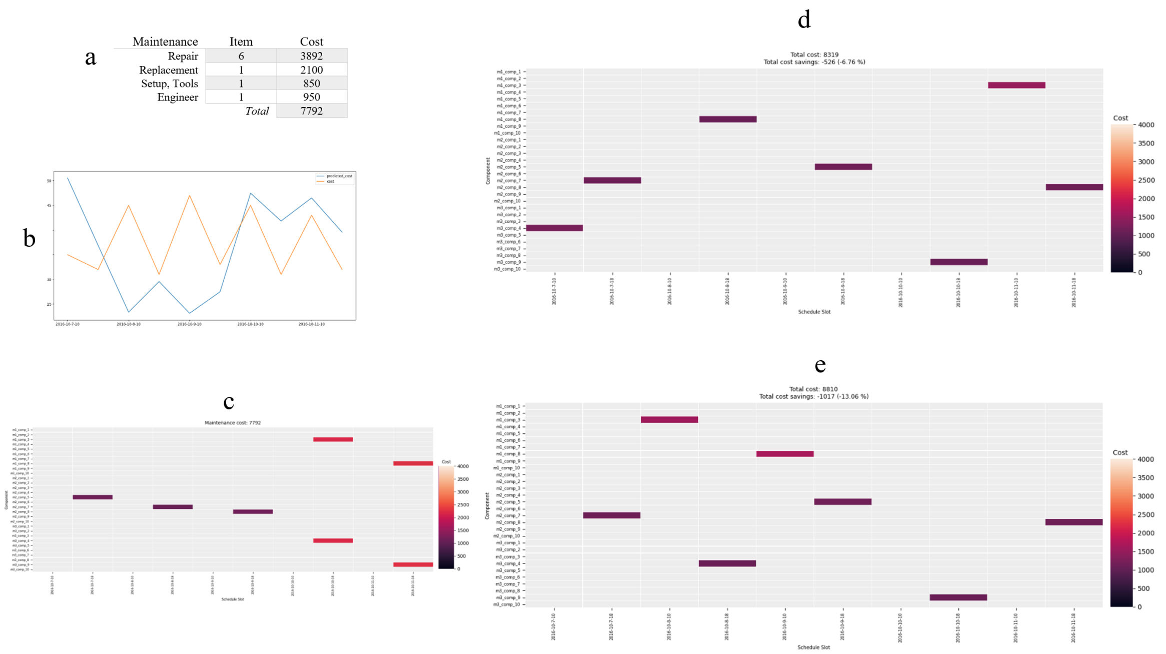


Fig. 7.8 Results of case 6

7.3.1.7 Case 7 - four machines with multiple components including business hour operation scheduling

Using the CNC machines with multiple components case in Section 7.3.1, the input choices considered for the scenario case include four machines with multiple components, maintenance activity after business hour, cost for engineer, setup, individual repair/replacement and associated timeslot as illustrated in Figure 7.9 (a).

Based on the input choices, the results are presented in Figure 7.9. Subfigure (b) depicts the overall predicted cost comparison between the optimized cost (i.e. subfigure d) and actual cost (i.e. subfigure c) over the same period. Subfigure (c) shows maintenance schedule over the 5 days period without optimization, whereas the optimization options can be achieved over 27% cost saving in subfigure (d) and over 14% cost saving in subfigure (e) with different slots over the same parameters and period respectively.

7.3.1.8 Case 8 - four machines with multiple components after business hour operation scheduling

Using the CNC machines with multiple components case in Section 7.3.1, the input choices considered for the scenario case include four machines with multiple components, mainte-

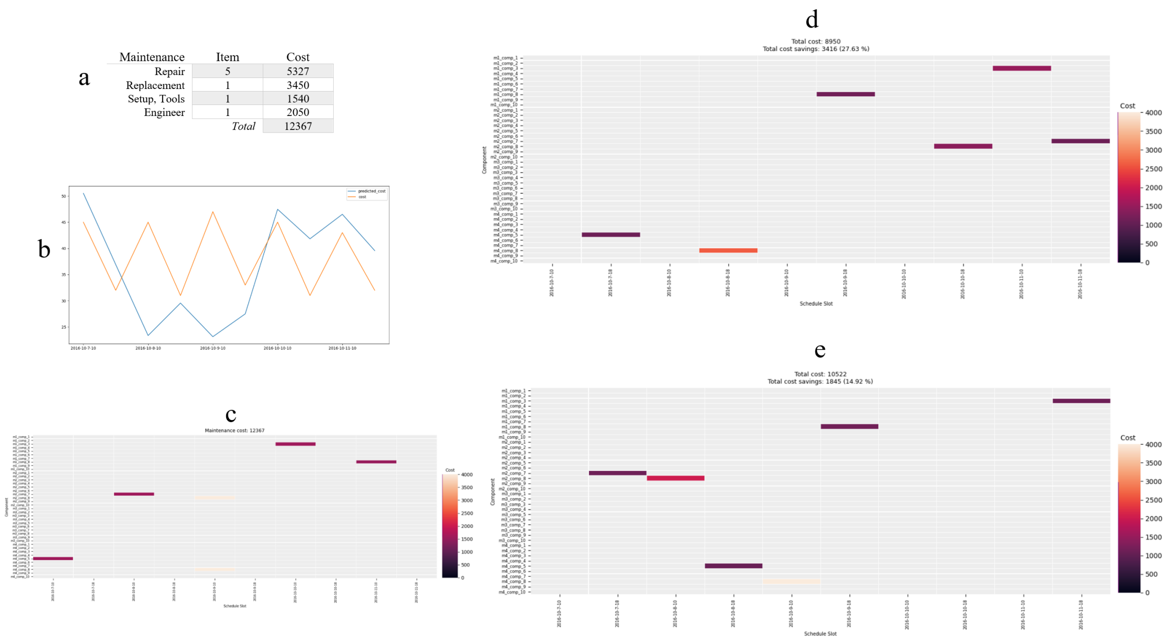


Fig. 7.9 Results of case 7

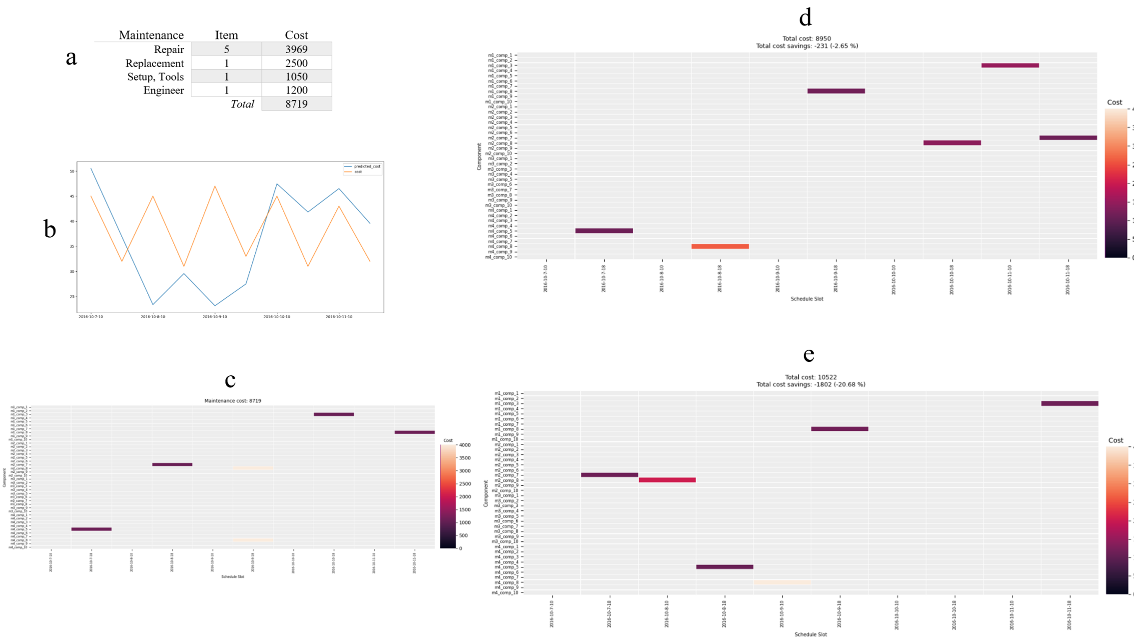
nance activity after business hour, cost for engineer, setup, individual repair/replacement and associated timeslot as illustrated in Figure 7.10 (a).

Based on the input choices, the results are presented in Figure 7.10. Subfigure (b) depicts the overall predicted cost comparison between the optimized cost (i.e. subfigure d) and actual cost (i.e. subfigure c) over the same period. Subfigure (c) shows maintenance schedule over the 5 days period without optimization, whereas the optimization options can be achieved over 2% cost saving in subfigure (d) and over 20% cost saving in subfigure (e) with different slots over the same parameters and period respectively.

7.3.1.9 Case 9 - four machines with multiple components with business hour operation for the initial slots scheduling

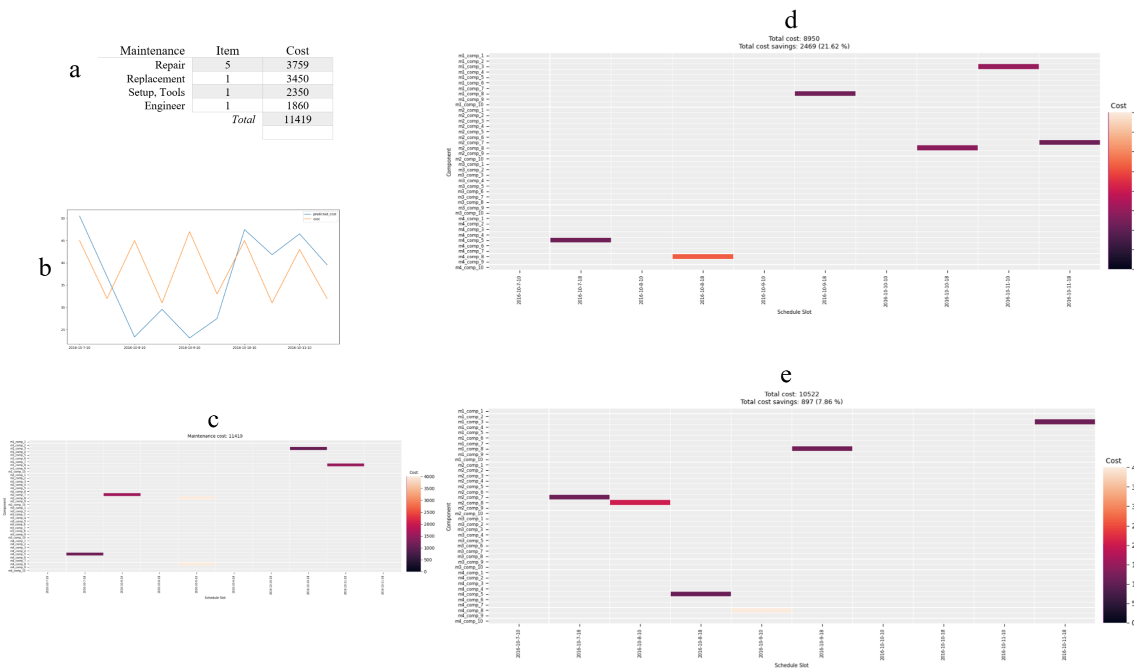
Using the CNC machines with multiple components case in Section 7.3.1, the input choices considered for the scenario case include four machines with multiple components, maintenance activity with business hour operation for the initial slots, cost for engineer, setup, individual repair/replacement and associated timeslot as illustrated in Figure 7.11 (a).

Based on the input choices, the results are presented in Figure 7.11. Subfigure (b) depicts the overall predicted cost comparison between the optimized cost (i.e. subfigure d) and actual cost (i.e. subfigure c) over the same period. Subfigure (c) shows maintenance schedule over the 5 days period without optimization, whereas the optimization options can be achieved



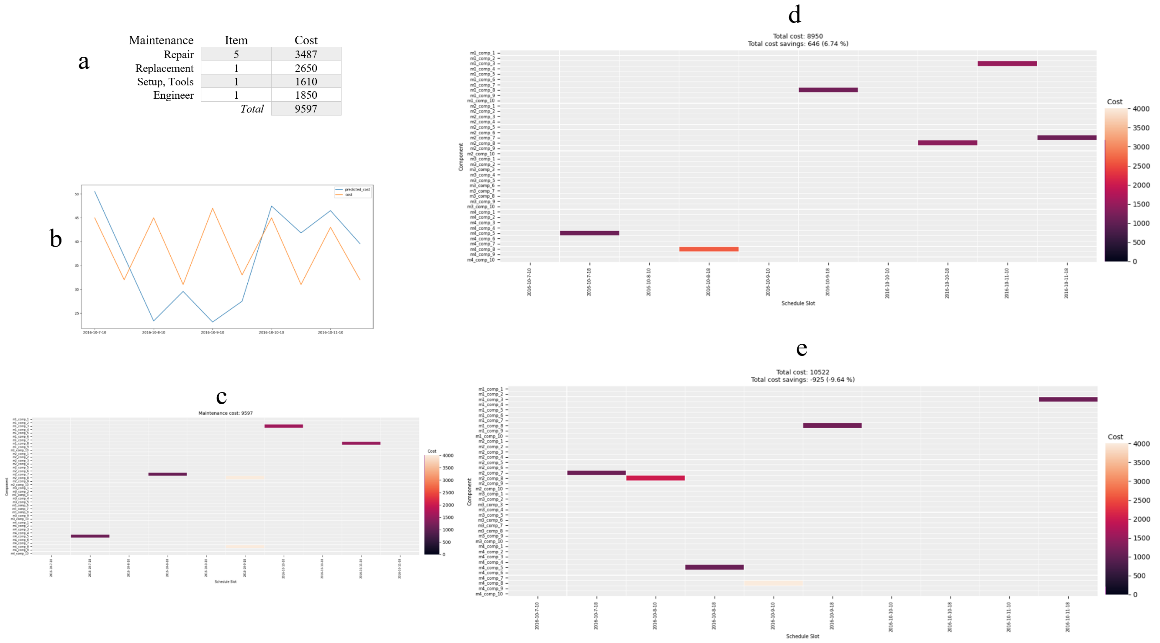
Maintenance	Item	Cost
Repair	5	3969
Replacement	1	2500
Setup, Tools	1	1050
Engineer	1	1200
Total		8719

Fig. 7.10 Results of case 8



Maintenance	Item	Cost
Repair	5	3759
Replacement	1	3450
Setup, Tools	1	2350
Engineer	1	1860
Total		11419

Fig. 7.11 Results of case 9



Maintenance	Item	Cost
Repair	5	3487
Replacement	1	2650
Setup, Tools	1	1610
Engineer	1	1850
	Total	9597

Fig. 7.12 Results of case 10

over 21% cost saving in subfigure (d) and over 7% cost saving in subfigure (e) with different slots over the same parameters and period respectively.

7.3.1.10 Case 10 - four machines with multiple components with business hour operation for the last slots scheduling

Using the CNC machines with multiple components case in Section 7.3.1, the input choices considered for the scenario case include four machines with multiple components, maintenance activity with business hour operation for the last slots, cost for engineer, setup, individual repair/replacement and associated timeslot as illustrated in Figure 7.12 (a).

Based on the input choices, the results are presented in Figure 7.12. Subfigure (b) depicts the overall predicted cost comparison between the optimized cost (i.e. subfigure d) and actual cost (i.e. subfigure c) over the same period. Subfigure (c) shows maintenance schedule over the 5 days period without optimization, whereas the optimization options can be achieved over 6% cost saving in subfigure (d) and over 9% cost saving in subfigure (e) with different slots over the same parameters and period respectively.

7.3.1.11 Summary of Experiment Scenario Cases for FIRST Flexible Manufacturing Case

We have done extensive experiment with different scenario cases using the application case and corresponding results i.e. Figure 7.3 , Figure 7.4, Figure 7.5, Figure 7.6, Figure 7.7, Figure 7.8, Figure 7.9, Figure 7.10, Figure 7.11 and Figure 7.12 in Section 7.3.1 are compiled in Table 7.5. The description describes the state of multiple machines/components for the maintenance. The Scenario(input) refers the different scenario cases including the input selection, RUL, with/out business hour schedule slot, number of machines components and corresponding maintenance window period for maintenance. The Maintenance refers to the type of the maintenance associated with the machines/components for the case. The Item is the number of machines/components required for maintenance. The Maintenance cost (i.e. without optimization) represents the overall maintenance cost including each individual maintenance cost i.e. repair/replacement, engineer, setup. The last column (i.e. with optimization) represent the maintenance options available for the maintenance with/out optimization. With optimization also provides maintenance options including the minimal cost and downtime impact cost for the corresponding maintenance cases.

For Maintenance Analysis, scenarios such as MCMIBHOSC, MCBHOSC (i.e. one CNC machine case in Table 7.2), MMCMIBHOSC and MMCBHOSC (i.e. two CNC machines components case in Table 7.3) are available for the decision maker in assisting planning as presented in Figure 7.3 , Figure 7.4, Figure 7.5 and Figure 7.6. The results are based on dynamic options i.e. based on RULs and inputs which illustrates options including five days periods with different costs. The maintenance costs are also driven by constraints such as resource, availability.

MCMIBHOSC offers an option for the different time slots with a consideration of less resource i.e. less cost (e.g. after business hour, resource i.e. setup cost which covers the engineer, downtime of each group. On the other hand, MCBHOSC offers different slots, including different resource constraint i.e. costs. The output of MCMIBHOSC in Figure 7.3 (c) offers no cost-saving whereas Figure 7.3 (d) presents over 1% cost-saving of the expected cost based on the 5 days period window. Similarly, the output of MCBHOSC Figure 7.4 (d) offers a substantial over 30% cost-saving of the same planning window, compared to Figure 7.4 (c) and MCMIBHOSC.

In the case of multiple machines components scenario cases (i.e. two or more CNC machines with multiple components) such as 2MMCMIBHOSC, 4MMCMIBHOSC offer different optimized options for the different time slots with a consideration of less resource i.e. less cost (e.g. after business hour, resource i.e. setup cost which covers the engineer,

Table 7.5 Summary of the experiment cases using PMS4MMC for predictive maintenance scheduling

Case	Description	Scenario (input)	Maintenance	Item	Maintenance cost - without optimization	With Optimization
1	Multiple machine components	RUL values of 5 different components, Minimal business hour/downtime impact, Different schedule slots with associated cost	Repair, Replacement	5	\$7871	*Option 1:* \$7751 (1.52%), Minimal cost impact *Option 2:* \$9869 (-25.38%) Minimal downtime impact
2	Multiple machine components	RUL values of 5 different components, Minimal business hour/downtime impact, Different schedule slots with associated cost	Repair, Replacement	5	\$11168	*Option 1:* \$7751 (30.59%), Minimal cost impact *Option 2:* \$9669 (11.63%) Minimal downtime impact
3	2 machines with multi-components	RUL values of 6 different components, Minimal business hour/downtime impact, Different schedule slots with associated cost	Repair	6	\$4581	*Option 1:* \$4581 (0%), Minimal cost impact *Option 2:* \$5714 (-24.73%) Minimal downtime impact
4	4 machines with multi-components	RUL values of 6 different components, Minimal business hour/downtime impact, Different schedule slots with associated cost	Repair	6	\$9526	*Option 1:* \$7400 (22.31%), Minimal cost impact *Option 2:* \$8192 (14%) Minimal downtime impact
5	3 machines with multi-components	RUL values of 7 different components, Minimal business hour/downtime impact, Different schedule slots with associated cost	Repair, Replacement	7	\$10635	*Option 1:* \$8319 (21.78%), Minimal cost impact *Option 2:* \$8810 (17.16%) Minimal downtime impact
6	3 machines with multi-component	RUL values of 7 different components, Minimal business hour/downtime impact, Different schedule slots with associated cost	Repair, Replacement	7	\$7792	*Option 1:* \$7792 (0%), Minimal cost impact *Option 2:* \$8810 (-13.06%) Minimal downtime impact
7	4 machines with multi-components	RUL values of 7 different components, Minimal business hour/downtime impact, Different schedule slots with associated cost	Repair, Replacement	7	\$12367	*Option 1:* \$8950 (27.63%), Minimal cost impact *Option 2:* \$10522 (14.92%) Minimal downtime impact
8	4 machines with multi-components	RUL values of 7 different components, Minimal business hour/downtime impact, Different schedule slots with associated cost	Repair, Replacement	7	\$8719	*Option 1:* \$8719 (0%), Minimal cost impact *Option 2:* \$10522 (-20.68%) Minimal downtime impact
9	4 machines with multi-components different inputs	RUL values of 7 different machines components with initial business hour/downtime impact, Different schedule slots with associated cost	Repair, Replacement	7	\$11419	*Option 1:* \$8950 (21.62%), Minimal cost impact *Option 2:* \$10522 (7.86%) Minimal downtime impact
10	4 machines with different inputs	RUL values of 7 different machines components with last business hour/ downtime impact, Different schedule slots with associated cost	Repair, Replacement	7	\$9526	*Option 1:* \$8950 (6.74%), Minimal cost impact *Option 2:* \$10522 (-9.64%) Minimal downtime impact

downtime of each group. The outputs of 2MMCMIBHOSC and 4MMCMIBHOSC include two different cost optimized options with different schedule slots and the associated cost.

The outputs of 2MMCMIBHOSC in Figure 7.5 (c) offers the standard cost accounted for the maintenance based on the input selection, whereas Figure 7.5 (d) and (e) offer over 29% and 11% cost-saving of the standard cost based on the 5 days period window. However, Figure 7.5 (d) certainly include different schedule slots over different 5 days whereas Figure 7.5 (e) minimizes the maintenance operation schedule slots within 3 days i.e. minimal downtime impact of the 5 days period window. Similarly, the output of 4MMCMIBHOSC Figure 7.6 (d) and (e) offer cost-saving options (over 22% and 14% respectively) with different schedule slots and associated cost, compared with the standard maintenance cost in Figure 7.6 (b) of the same planning window.

In the case of optimal downtime, the overall maintenance cost can however be higher than the actual maintenance cost as the scenario cases such as case 1 (i.e. Figure 7.3), 3, 5 and 7 show in the experiment summary at Table 7.5. In these cases, if maintenance operation is required based on minimal impact of maintenance time windows i.e., downtime, regardless the cost of resources and impact of production, the overall cost for the maintenance time slot including business hour, resource i.e., the engineer, tools, and downtime of each maintenance group cost more than alternative options e.g., optimized cost in Figure 7.3 (d) or actual cost in Figure 7.3 (c) in Section 7.3.1.1. As a result, the optimal downtime should be considered when maintenance activity is urgent and downtime with associated cost is manageable.

The additional cases (i.e. 5 – 10) in Table 7.5 with the corresponding results demonstrate the verification of our solution, providing predictive maintenance scheduling plan with optimization with the different cases and input selections.

The optimization comparison i.e., cost from scenario cases (i.e. subfigures (c)s and (d)s in Figure 7.3, Figure 7.4, Figure 7.5 , Figure 7.6) consistently demonstrate that an overall cost-saving can be made if predictive maintenance activity is performed upon an optimal choice. This offers the corresponding engineer the ability to make appropriate maintenance decisions based on the business needs i.e. minimal downtime, cost, etc., since *PMS4MMC* supports *dynamic maintenance* by allowing the manipulation of different inputs (i.e. *dynamic predictive maintenance scheduling* in Section 7.2.3.2).

7.3.2 Applying PMMI 4.0 and PMS4MMC with Virtual Factory Predictive Maintenance Case

Monitoring status of different machines and different components in a machine in a collaborative network or a virtual factory is a similar activity as monitoring machines in a factory

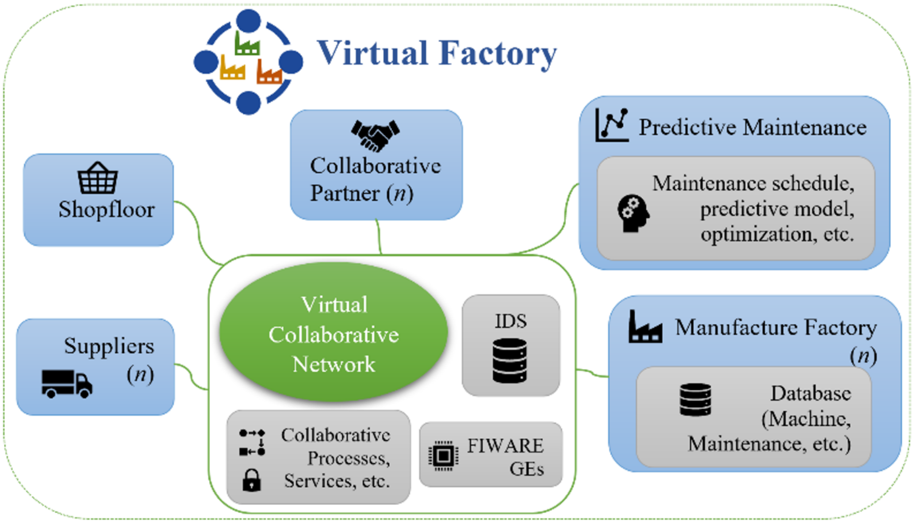


Fig. 7.13 A reference architecture for a virtual factory with a predictive maintenance service (Sang et al., 2021*b*)

(i.e. the application case). We have applied our proposed *PMMI 4.0* and *PMS4MMC* for supporting Virtual Factory using FIRST Virtual Factory Case in Section 3.2 in Chapter 3 and subsequently published the work in *PRO-VE 2021 (22nd IFIP/SOCOLNET Working Conference on Virtual Enterprises, Smart and Sustainable Collaborative Networks 4.0, November 2021)*. A predictive maintenance service within a collaborative manufacturing network that offers flexible and modular components for optimizing maintenance service. A manufacturing case is used to demonstrate that predictive maintenance service can be integrated using a modular fashion into FIWARE framework and maintenance schedule plans can be created by accessing distributed data in the collaborative network as described in Figure 7.13.

7.3.2.1 Virtual Factory maintenance case

Consider the scenario from the case study (Sang et al., 2021*b*), RUL values i.e. predicted value in day of the machine components are identified over a time window of 5 days period. Maintenance schedule should be planned and allocated to 5 different days period for the maintenance activities. In this scenario, 4 repairs and 1 replacement maintenance are considered. The maintenance activity i.e. repair, or replacement can also be decided by a maintenance engineer based on the predicted RUL information and other related maintenance information.

In the context of applying *PMS4MMC*, all the machine components are scheduled within their RUL period to avoid substantial maintenance and related costs such as downtime, setup, etc. The costs extracted from the case data from the maintenance dataset includes multiple factory machine components, resource index, maintenance task, timestamps, and related cost. RUL values of the machine components are mostly utilized for the scheduling as the cost of RUL is relatively less. Group maintenance i.e., time window over 5 days with 2 available maintenance slots per day, and optimizations such as location-based based on resource index i.e., factory location/dependency are applied to reduce high value of setup/location cost. This enables the model to minimize the number of set-ups with associated other costs including location maintenance.

7.3.2.2 Result of Virtual Factory maintenance case

The optimal result is presented in Figure 7.14. The subfigure (c) illustrates the normal maintenance schedule without optimization whereas the subfigure (d) represents the optimal maintenance schedule. The maintenance costs include the individual cost (repair or replacement) and setup cost which covers the 2 engineers for covering different maintenance tasks, downtime of each group. The optimal maintenance schedule plan i.e. minimal cost impact can save over 12% of the standard cost (i.e. subfigure (d)) whereas the optimal option for minimal downtime impact (i.e. subfigure (e)) save over 10%, based on the 5 days period window. Based on the prediction in subfigure (b), the optimal approach suggests that the overall maintenance cost can be saved over the period for the maintenance activities. As business needs, the maintenance engineer or operator can ultimately make appropriate maintenance decision.

7.3.3 Performance Evaluation of PMS4MMC

In this section, we evaluate the performance of *PMS4MMC* algorithms i.e., the overall performance of the algorithms utilized for *PMS4MMC* maintenance scheduling in Section 7.3.3.1. The impact of maintenance scheduling optimization for optimal cost and down time and the performance comparison with different optimization packages for the optimal cost and down time over the scenario cases are presented in Section 7.3.3.3. Performance comparison analysis with existing approaches is presented in Section 7.3.4 Based on the evaluation outcomes, it shows that algorithms are applicable to different industrial scenario cases. We can therefore conclude about their applicability to various industrial cases and effectiveness in supporting predictive maintenance scheduling for Industry 4.0 multiple machines and components (*PMS4MMC*).

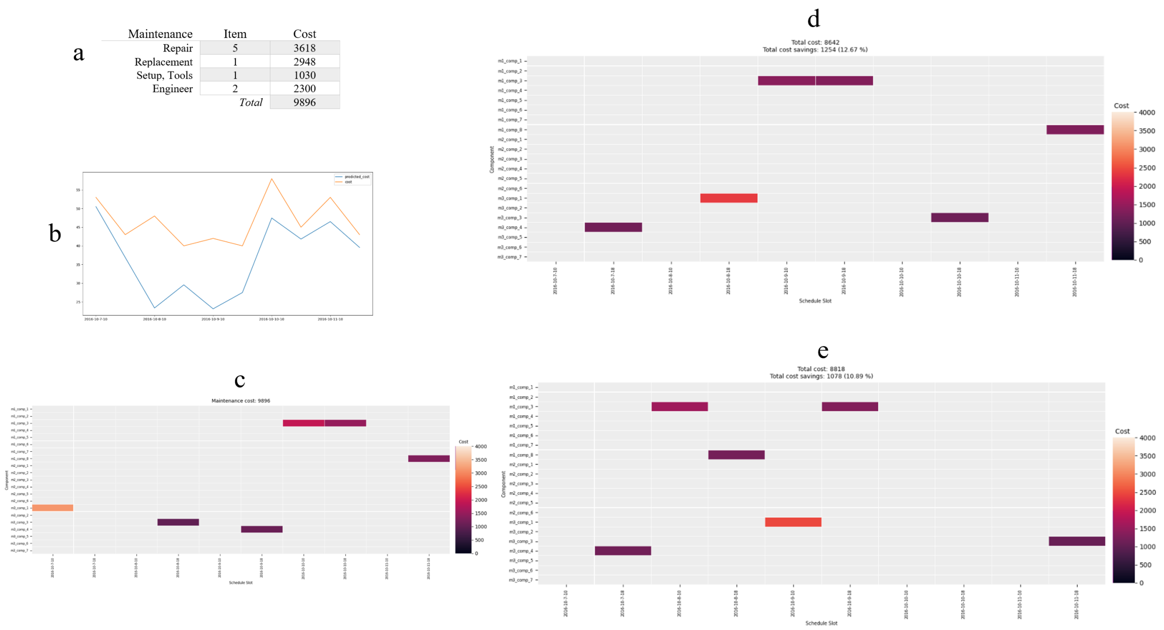


Fig. 7.14 Results of virtual factory maintenance scheduling case

7.3.3.1 Complexity of PMS4MMC Algorithm

The complexity of algorithms measures the performance which generally involves assessing their capacity in terms of different parameters such as scalability and efficiency (Brewka, 1996; Pinedo, 2016). Algorithm complexity is a function *f(n)* for measuring time and space used by an algorithm regarding the input size n, and the time and space required by the algorithm to run is computed. The time/space required by the algorithm depends on the input size *(n)* which is available for producing the output. In a given function, $n \rightarrow f(n)$ where n = the input size, *f(n)* is either the average-case complexity i.e. average amount of resources required for the input size n or the worst-case complexity i.e. maximum number of resources required for the input size n of the algorithm.

In the context of time complexity, *T(n)* time complexity is determined by the computation time that requires to execute an algorithm. The time complexity is generally computed by counting the elementary operations of the algorithm. In this instance, the number of steps or operations that requires to process the input(s) for the output. An estimated time required for each operation is defined, and all steps required for each operation is assumed to be constant. The input i.e. size of the input determines varied computation time, given a function: *O(n)* where O = the time and n is the input size.

In relation to the time computation, it depends on the input sizes to the elementary operation of the algorithm. The elementary operation is that operation which the algorithm performs. In the case of *PMS4MMC*, the algorithm processes the scheduling optimization by producing an optimal maintenance schedule plan based on the maintenance items and associated maintenance time, cost and availability. The scheduling optimization time is assumed constant regardless of the input size of the constraints being checked. The time complexity of each algorithm is therefore given by $T(n) = n - 1$. Hence, by assuming that each step scheduling optimization has the size $O(1)$, the overall complexity can be $O(nn)$. Although the complexity does require a significant amount of computing power, it is a general issue for scheduling algorithms (Brewka, 1996; Pinedo, 2016). Nowadays increasing computing power and elastic computing power solutions are available, which benefit the users. Moreover, in real life, providing some constraints for partial scheduling solutions is more desirable.

Deterministic inputs are used for computation to be achieved in feasible time. Regarding *PMS4MMC* algorithm, the number of steps taken by the number of machines required for maintenance over a period with optimal resource and cost determines how much time is required. To achieve maintenance scheduling optimization in polynomial time, inputs with different maintenance checks are used. For example, from multiple maintenance assets processing i.e., *Algorithm 3*, only item which requires maintenance is considered. Moreover, only maintenance required items are considered for scheduling processing, instead of considering the entire maintenance assets which makes it feasible for traceable and deterministic states. Similarly, the available resources such as engineer, tools for the maintenance operation are considered as opposed to the whole resources in the maintenance availability processing i.e., *Algorithm 5*. In the same manner, the maintenance processing i.e., time in *Algorithm 4* and cost in *Algorithm 6* consider certain constraints such as valid maintenance tasks with optimal maintenance cost or user inputs of valid maintenance tasks with associated cost are considered.

In the next Section 7.3.3.2, using the industrial scenario cases i.e., Section 3.1 and Section 3.2 of Flexible Manufacturing and Virtual Factory of the FIRST project, *PMS4MMC* algorithms are evaluated. The input parameters used are a combination of maintenance business cases including multiple machines components operating in product line, several maintenance related inputs such as maintenance time windows, maintenance task, maintenance cost and different resources such as engineer, tools, spares, etc. and the availability of maintenance operation and related resources as shown in Figure 7.3 (a), Table 7.1 in Section 7.3.1.

Fig. 7.15 Overall performance of maintenance scheduling optimization for optimal (minimal) cost and downtime

7.3.3.2 Impact of predictive maintenance scheduling optimization for optimal(minimal) cost and downtime

To evaluate the performance of the maintenance scheduling optimization, we utilize the results of the scenario cases used in Figure 7.3, Figure 7.4, Figure 7.5 , Figure 7.6 and Figure 7.14 and Table 7.5 (i.e., summary of the flexible manufacturing case) in Section 7.3.1 for analysis. In this instance, the impact of the maintenance scheduling performance regarding the optimal (minimal) cost and downtime against the computation (i.e., the average execution time of the scheduling optimization) and maintenance overall cost of all cases from both flexible manufacturing and virtual factory of the FIRST project is considered.

Regarding the average execution time of the scheduling optimization, the overall actual execution of the scheduling optimization with associated algorithms 1 - 6 (i.e., Section 7.2.3) regarding multiple machines/components, available maintenance time windows, maintenance resources such as engineer, tools, cost, etc., is considered. In this instance, the maintenance engineer/user provides the desired input selections i.e., pending maintenance items with the desired maintenance time windows, task, and associated cost with the maintenance resources i.e., engineer, tools, etc. The performance result is presented in Figure 7.15.

The result depicts that the optimal cost over all cases offers cost-saving, compared with the optimal downtime with related average execution time. Multiple machines with multiple components (i.e., 5 – 8 machine components of different machines) with pending maintenance serves as the initial inputs, which then drives maintenance scheduling optimization processing i.e., task, time, and cost with associated maintenance resources i.e., engineer, tools, and availability processing. Regarding the maintenance scheduling optimization execution, the average execution time is mostly consistent over all cases, apart from cases (i.e., include multiple machine components, from two machines with multiple components to four machines with multiple components of the product line case) including *Case 4, Case 5, Case 7, Case 8, Case 9 and Case 10* whereas the average execution time deviates slightly.

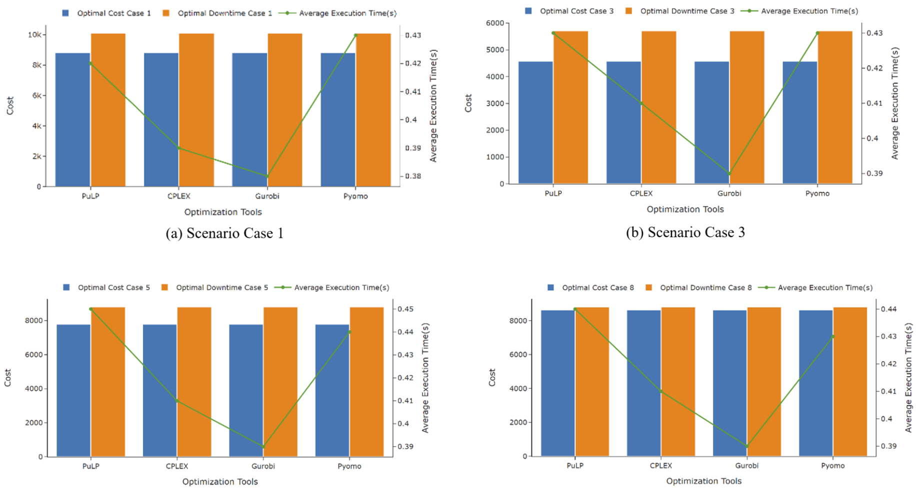
Besides, the results verify the applicability and efficiency of *PMS4MMC*. Based on the results, the maintenance decision maker or user can use the optimal cost scheduling optimization option if no urgent maintenance will be required for the future maintenance plan. On the other hand, the optimal downtime optimization option is desired if minimal interruption of factory operation is required, and maintenance cost can be manageable.

7.3.3.3 Performance comparison with optimization packages for optimal (minimal) cost and downtime

In this section, we evaluate and compare some popular optimization packages that can be used for *PMS4MMC* scheduling optimization. Most of the widely used optimization packages by the industrial and research community include: *PuLP, CPlex, Gurobi and Pyomo*. *PuLP* is open-source python library for mathematical modelling and optimizations (PuLP, 2021) whereas *CPlex* is IBM software package, available for both community and commercial licenses (Cplex, 2021). It supports both mathematical modelling and optimizations. Similarly, *Gurobi* is another popular commercial product that supports both mathematical modelling and optimization (Gurobi, 2021). *Pyomo* is another python-based open-source software package which is mainly used for various scientific, and research works (Pyomo, 2021).

To evaluate the performance of the maintenance scheduling optimization, we use the scenario cases *1, 3, 5 and 8* at Table 7.5 (i.e. summary of the flexible manufacturing case) in Section 7.3.1 for performance analysis. In all instances, the overall performance impact of the maintenance scheduling optimization over the optimal(minimal) cost and downtime of all cases from the FIRST project is considered.

The overall performance results are presented in Figure 7.16. In all cases, the commercial tool, *Gurobi* outperform all the other open-source optimizations where *CPlex* is the second-best optimization over the four tools. *PuLP* is consistently average, where *Pyomo* is slightly better than *PuLP*. It can thus be noted that *Gurobi* and *CPlex* can offer higher performance, compared with *PuLP and Pyomo*. Industrial implementation can be optimized by adopting the commercial offered *Gurobi or CPlex* with the required commercial license. On the other hands, *PuLP and Pyomo* can offer the open-source option with compromised performance and fewer support for different built-in libraries. All the experiment cases in Section 7.3.1 and Section 7.3.2 currently use the python *PuLP* package, in which the overall performance is slightly lower than *Gurobi* as shown in Figure 7.16. For an optimized performance,



(a) Scenario Case 1
(b) Scenario Case 3
(c) Scenario Case 5
(d) Scenario Case 8

Fig. 7.16 Overall performance of optimization tools with scenario cases for optimal (minimal) cost and downtime

PMS4MMC implementation will be updated with *Gurobi* package upon acquiring the required commercial license.

7.3.4 Comparison with existing maintenance scheduling optimization approaches

To evaluate the applicability and effectiveness of our proposed *PMS4MMC* method, we compare our approach with some of the most recent works in the field of manufacturing in the research community. We utilize the key elements that are essential to operating Industry 4.0 predictive maintenance as previously discussed in Section 7.1 (including Section 5.1.1 in Chapter 5) as well as the key factors considered (data-driven predictive, multiple machines/components, maintenance task, cost, time, availability, resources, and dynamic scheduling) as discussed in Section 7.1.2. The related works include:

- ***A*** Maintenance scheduling optimization for single machine with multiple components, structural dependence was focusing on the situation where the replacement of a certain component requires the dismantling or replacement of other components (Dekker et al., 1997*b*). Maintenance scheduling is optimized based on model-driven approach which relies on domain experts and physical structure of the machine.

- ***B*** Maintenance scheduling optimization for a multi-component system where a component failure can lead to failures of other components, part of stochastic dependence -

the deterioration or failure processes of components are (partially) dependent. According to three different scenarios: no damage is caused and only the failed component requires a replacement, the component failure causes one other component to be replaced as well, or the component failure leads to a complete system replacement (Van Horenbeek and Pintelon, 2013).

C Maintenance scheduling optimization for a system that is subject to economic dependence when maintaining several components simultaneously leads to higher costs than maintaining them separately (Dekker et al., 1997*a*). Such negative economic dependence can be present in systems with manpower restrictions, safety requirements, or production losses, which are usually incorporated via restrictions in the maintenance model.

D Camci (2009) considers the case in which (i.e., structure dependence) a component is stopped due to failure or maintenance of another component. Based on the probability of another component, maintenance is planned for preventive activity. However, more situations (i.e., technical, performance, etc.,) exist in which components are dependent through the physical structure of the system.

E Mourtzis et al. (2017) proposes an integrated predictive maintenance system, under the concept of Industry 4.0, that utilizes data gathered from the monitored equipment and adjusts the maintenance schedule upon timeslot availability.

F Senra et al. (2017) proposes an approach that considers available equipment with support technicians, as well as the related processing times for the schedule process. The proposed approach was illustrated with a case study however lacks equipment monitoring for analytics.

G A method for decision-making tool was proposed for production maintenance synchronization (Levrat et al., 2008). It utilizes multiple criteria such as product performance and component reliability for producing an optimal scheduling plan.

H In the context of flexible job shop scheduling, ZHENG et al. (2013) focus on a scheduling problem incorporating a condition-based maintenance approach for providing the optimal solution. However, it lacks the consideration for the applicability of different types of machines and the overall schedule for producing new maintenance schedule.

I Approach for complex systems by employing discrete time Markov chain models for modelling multiple degradation processes of components and a Bayesian network model for predicting system reliability (Lee and Pan, 2017). Bayesian network is repeatedly used over time for evaluating system reliability and the inter-time–slice connection of the same node is monitored by a sensor. Limitations such as computation.

J Lindström et al. (2017) addresses intelligent and sustainable production in the sense of combining and integrating online predictive maintenance and continuous quality control. The objective is that continuous quality control can provide input to the online predictive maintenance in cases where no signs of maintenance issues have been indicated and inadequate output is produced (and the process parameters cannot be adjusted to meet the output specifications). i.e., diagnosing and planning action, of an action research effort at a manufacturing company, Gestamp HardTech AB, which produces advanced and complex press hardened components for the vehicle industry

K Ji and Wang (2017) consider a less error-prone scheduling procedure in which input data is contrasted to failure patterns detected by a procedure in databases of previous runs of the system. In a real manufacturing shop floor, the main tasks include task scheduling, material handling, machining, and inspection. Basically, the task scheduling considers the currently available equipment, where the cost and time are the main objectives.

L A predictive maintenance system which is based on Internet of things technology to change the existing coal mine equipment maintenance mode. System is mainly composed of equipment state monitoring station, coal mine monitoring center, re-mote predictive maintenance system. Mine monitoring center collect parameters information from the equipment monitoring sub-station and connect to the remote predictive maintenance center through the wireless network or cable. Remote predictive maintenance center obtain the monitoring data by communicating with mine monitoring terminal, and the analysis results were sent to the database (Dong et al., 2017).

M Using Markov processes, the state probabilities are calculated and the optimal value of the mean time to preventive maintenance is determined by maximizing the availability of single component with respect to mean time to minimal preventive maintenance. Using the state probabilities, the problem is set up as Markov decision processes and an optimum maintenance policy using the policy iteration algorithm is determined (Chan and Asgarpoor, 2006).

Table 7.6 shows the comparison between our approach *PMS4MMC* and some existing approach in the field of manufacturing. In relation to ***data-driven predictive***, approaches such as ***G, H, I, J, K, and L*** use different traditional condition-based/machine learning approaches

Table 7.6 Comparison between the proposed *PMS4MMC* approach and some existing approaches for Industry 4.0 Predictive Maintenance Scheduling

	Approach	Data-driven predictive	Multiple machines/ components	Maintenance cost, time, task	Availability of maintenance	Maintenance resource	Dynamic maintenance scheduling	Industry 4.0 Applicability
A	Single Machine Multiple Component with structure dependency (Dekker et al., 1997*b*)	x	L	x	x	x	x	x
B	Multi-component system with stochastic dependence (Van Horenbeek and Pintelon, 2013)	x	L	L	x	x	x	x
C	Multi-component system with economic dependence (Dekker et al., 1997*a*)	x	L	x	x	x	x	x
D	Maintenance based on multi-component system and structure dependency (Camci, 2009)	x	L	x	x	x	x	x
E	Factory maintenance schedule upon timeslot availability (Mourtzis et al., 2017)	x	L	x	L	x	L	L
F	Schedule approach with available equipment, technicians and processing times (Senra et al., 2017)	x	L	L	L	L	L	x
G	Multiple criteria i.e., product performance, component reliability for scheduling (Levrat et al., 2008)	S	L	x	x	x	x	x
H	Flexible job shop scheduling, incorporating a condition-based (ZHENG et al., 2013)	S	L	L	x	x	L	x
I	Modelling multiple degradation of components using a Bayesian network model (Lee and Pan, 2017)	S	x	x	x	x	x	x
J	Online predictive maintenance and continuous quality control (Lindström et al., 2017)	S	x	x	x	x	L	x
K	Failure patterns detected by a BDA procedure in databases the system (Ji and Wang, 2017)	S	x	x	x	L	L	x
L	Equipment state monitoring and maintenance mode over internet (Dong et al., 2017)	L	x	x	x	x	x	x
N	Markov decision process and maintenance policy for single component (Chan and Asgarpoor, 2006)	x	L	x	x	x	x	x
	Our approach – PMS4MMC	S	S	S	S	S	S	S

Data-driven Predictive	Maintenance scheduling is driven by predictive model, data such as maintenance, etc.
Multiple Machines/Components	Support maintenance scheduling for multiple machines/components
Maintenance Cost, Time, Task	Consider maintenance cost and time with associated task
Availability of Maintenance	Consider availability of maintenance operation, resources such as engineer, tools, spares, etc.
Maintenance resource	Consider maintenance resources such as engineer, tools, spares, etc.
Dynamic maintenance scheduling	Consider the ability to dynamically scheduling maintenance i.e., different parameters, etc.
Industry 4.0 Applicability	Applicable for Industry 4.0 predictive maintenance scheduling
L	Limited or only some features are supported for the factor or concept for Industry 4.0
S	Support for the factor or concept for Industry 4.0
x	No support or applicable for the factor or concept for Industry 4.0

utilizing data such as failure or degradation data of machine component. Approaches such as ***E and F*** utilize manufacturing data such as availability of equipment, technician, and timeslot with no consideration for the aspect of predictive model. Moreover, these approaches focus on the manufacturing context itself, and hence will suffer from adapting to complex Industry 4.0 environment as large amount of data produced by data exchange and process occurred among the various machine equipment tools involved in Industry 4.0 manufacturing and then these data need to be handled, and developed predictive models which require advanced methods i.e., big data processing, deep learning, etc. (Sang, Xu, de Vrieze and Bai, 2020*a*). In our approach, we however consider such capabilities by employing our proposed *PMMI 4.0* architecture platform with big data enabled processing, as well as modelling the predictive RUL method proposed in Chapter 6. The primary goal of predictive maintenance is enabling potential detection of pending failure of machines/components which allows effective maintenance management to reduce downtime and cost (Sang et al., 2021*b*). As such, our method *PMS4MMC* best delivers a concrete predictive maintenance scheduling approach as demonstrated in the industrial cases in Section 7.3.1 (i.e. flexible manufacturing cases) and Section 7.3.2 (i.e. virtual factory case).

Regarding the aspect of ***multiple machines/components***, most of the approaches in Table 7.6 support multiple components or a single machine with multiple components for maintenance scheduling. Traditional approaches such as ***A, B, C, D, and N*** support single machine with multiple components focusing the aspect of dependencies such as structure, stochastic, and economic whereas approach ***N*** is based on Markov decision policy for single component . Their approaches rely on the physical structure of the actual machine, and that leads to complexity. Moreover, reactive, or preventive maintenance is only considered. Thus, it cannot meet Industry 4.0 as several complex and advanced machines such as CPS, robot, CNC, etc., operate the factory operation in complex collaborative setting. Recent approaches such as ***E, F, H, and K*** offer alternative approach in which multiple components can be scheduled based on condition-based model i.e., detection of machine degradation threshold or factory data i.e., failure, etc. Similarly, most of the existing approaches still not address for the aspect of maintenance availability, cost, task, time, and resources. Approach ***B*** considers the maintenance task in a way that the dependency of the failure component (i.e., scholastic dependence) based on the physical degradation of the failure component. It however does not offer the support for maintenance availability, resources, or cost. In the case of approaches ***E, F, and H***, they consider the availability of maintenance i.e., schedule slot in ***E and H***, availability of resources such as technician, equipment, and time in approach ***F*** and time in ***H***. Maintenance cost with associated resources, task and time is ignored in the approaches. Thus, these approaches cannot meet the demands of Industry 4.0, as Industry 4.0 driven manufacturing systems are complex systems of interconnected machines or devices who interact and collaborate for business processes within the manufacturing network and that any failures can impact the entire manufacturing operation and can result in undesired downtime and costs to the manufacturing chain (Deloitte, n.d.; Mobley, 2002). To effectively manage Industry 4.0 maintenance, it is required to consider the aspect of the multiple machines/components operating in the factory, associated with related maintenance resources, task, time, cost, and availability. In this aspect, our method *PMS4MMC* (i.e., proposed in Section 7.2) delivers a concrete and verified approach as shown in the FIRST industrial cases including flexible manufacturing and virtual factory in Section 7.3.1 (i.e. flexible manufacturing cases) and Section 7.3.2 (i.e. virtual factory case), utilizing the factors considered for Industry 4.0 predictive maintenance scheduling optimization in Section 7.1.2.

In respect to ***dynamic maintenance scheduling*** at Table 7.6, traditional manufacturing system needs to move toward customized mass production for the same functional in the highly competitive world market. Industry 4.0 help manage the challenges, by making vertical, horizontal and end to end integrations between different components of manufacturing system and collaborative partners such as supplier, etc., and by using real-time data. Thus, flexibility as well as efficiency and high level of availability of system i.e., maintenance become more and more important. In this context, maintenance schedule plan must be flexible enough to respond to changes or needs when arise. Regarding existing approaches, approach ***E and F*** are designed in a manner that scheduling can be planned based on the availability of maintenance timeslot (***E***), equipment, technician, and time (for ***F***). These approaches may offer a certain of flexibility i.e., input selection, based on maintenance availability i.e., timeslot, equipment, etc., in the enterprise organization however do not consider the aspect of Industry 4.0. Similarly, approaches ***J and K*** offer database approach whereas maintenance schedule can be planned based on the configured i.e., condition-based threshold, machine equipment of the factory. Thus, their approaches can be cumbersome when it comes to managing Industry 4.0 focusing setting. On the hand other, our approach offers flexible options i.e., RUL, user input, alert monitoring, whereas the maintenance engineer can dynamically determine potential maintenance tasks, time windows and associated cost based the availability of maintenance operation based on business needs. The support for our method extends to Industry 4.0 virtual factory by allowing a collaborative factory where different adjustments i.e., maintenance schedule with different RULs of different pending failure period, maintenance associated with cost, resource availability, etc., can be adapted. The process is assisted by utilizing the predictive maintenance data model in Figure 5.2 in Chapter 5 as well as related data from databases as described in Figure 7.2 in Section 7.2.3, which is part of PMMI 4.0 in Figure 5.4 in Chapter 5. Hence, this makes our approach flexible enough to provide dynamic scheduling as respond to the challenges as demonstrated in the industrial cases in Section 7.3.1 (i.e. flexible manufacturing cases) and Section 7.3.2 (i.e. virtual factory case).

Based on the comparison analysis and results at Table 7.6, as well as the verified cases in Section 7.3.1 (i.e. flexible manufacturing cases) and Section 7.3.2 (i.e. virtual factory case), it demonstrated that the applicability and verification of our method *PMS4MMC* in real world industry setting. For future work, we plan to evaluate our approach with multiple production lines within collaborative manufacturing networks, particularly complex resources e.g., sharing multiple engineers, equipment tools, etc., across factories (within nearby location, etc.). We also plan to explore the aspect of intelligent maintenance i.e., automation e.g., integrating our approach with deep reinforcement learning, particularly integrating with maintenance monitoring (i.e., alert morning in *PMMI 4.0* in Figure 5.4 in Chapter 5) for applicable autonomous maintenance plan and execution.

7.4 Chapter Summary

In this chapter, we looked predictive maintenance scheduling for multiple machines/components involved in the Industry 4.0 environment, considering different key factors such as data-driven maintenance i.e., predictive models such as RUL, multiple machine components, the different maintenance aspect such as tasks, maintenance time, cost, as well as the availability of resource such as availability status of each components, engineer, etc.

- Section 7.2 provided the proposed *Predictive Maintenance Schedule for Multiple Machines and Components (PMS4MMC)* that supports the flexibility in dealing with complex systems and dynamic nature of Industry 4.0 in a modular fashion.

  PMS4MMC is part of the maintenance decision support in *PMMI 4.0* in Figure 5.4 in Chapter 5,

- Section 7.1.2 provided the key factors considered in optimal predictive maintenance scheduling in the context of Industry 4.0. Data-driven maintenance i.e. predictive models such as RUL, multiple machine components, different maintenance aspect such as tasks, maintenance time, cost as well as maintenance availability of resource such as availability status of each components, engineer were discussed for PMS4MMC.

- One key challenge to complex manufacturing is to design and develop embedded services that assist in the effective management of machine equipment tools in a flexible way (Koren et al., 2018; Mobley, 2002; Thoben et al., 2017; Zonta et al., 2020). *PMMI 4.0* was created based on the design and development of Industry 4.0 predictive maintenance that supports flexible integration of different components and processes for maintenance services (See Chapter 5).

  PMMI 4.0 is integrated with the proposed PMS4MMC based on a data-driven approach that takes into advantage of machine and maintenance data such as operation, condition, and maintenance data.

  Through the implementation of big data analytics on new data in the connected machine equipment tools, *PMS4MMC* benefits from *MPMMHDLA*, a modular predictive maintenance model utilizing deep learning (See Chapter 6) and scheduling optimizations to perform predictive maintenance.

- Section 7.3 provided the industrial cases such as Flexible Manufacturing and Virtual Factory that are used to demonstrate the validity of *PMMI 4.0* and *PMS4MMC*.

  In the scope of this work, we carried out different scenarios i.e. multiple components of a machine as well as multiple machines with multiple components derived from the maintenance data in the production line from FIRST industrial flexible manufacturing case, supporting dynamic maintenance scheduling by facilitating different input selections such as predictive RULs, user input machines as well as alert notification, *PMS4MMC* is proved to be working well with the industrial cases based on the results e.g. optimal cost up to 30% which offer different optimized schedule plans for maintenance decision makers.

At this stage, multiple product lines with multiple machines/components are considered as future work, particularly in the context of Collaborative Networks or Virtual Factories. This will bring further knowledge and validation to our work, and that will bring additional contributions to the research community.

Based on the verified outcomes in Section 7.3.1 (i.e. flexible manufacturing cases) and Section 7.3.2 (i.e. virtual factory case), *PMS4MMC* algorithms are applicable to different industrial scenario cases. In comparison with existing approaches in Section 7.3.4, our approach *PMS4MMC* is further proven for its validity. We can therefore conclude about their applicability to various industrial cases and effectiveness in supporting predictive maintenance scheduling for multiple machines and components, *PMS4MMC* in the context of Industry 4.0. Regarding the complexity of *PMS4MMC*, multiple product lines in the context of complex Industry 4.0 industries such as Collaborative Networks Manufacturing is to be evaluated, and potential optimizations will be made.

The contributions including journal/paper publications of this chapter includes:

- A list of key factors for Optimal Predictive Maintenance Scheduling in the context of Industry 4.0
- A method of Predictive Maintenance Schedule for Industry 4.0 Multiple Machines and Components *(PMS4MMC)*, applying the key factors
- Implement different modules in FIWARE for different maintenance schedule optimization
- Design a new predictive maintenance schedule for FIRST maintenance datasets, applying *PMS4MMC*
- Sang et al. 2021 A Predictive Maintenance Model for Flexible Manufacturing in the Context of Industry 4.0. Front. Big Data 4:663466. doi: 10.3389/fdata.2021.663466
- Sang et al. 2021. Supporting Predictive Maintenance in Virtual Factory, PRO-VE 2021 Smart and Sustainable Collaborative Networks 4.0, 22nd IFIP/SOCOLNET Working Conference on Virtual Enterprises, 22-24 November 2021
- Sang et al. 2020. Applying Predictive Maintenance in Flexible Manufacturing. Boosting Collaborative Networks 4.0. PRO-VE 2020. IFIP Advances in Information and Communication Technology. 203–212

Chapter 8

Conclusion and Future work

Based on a design science methodology, the preceding chapters have addressed the various challenges posed by maintenance in a complex Industry 4.0 manufacturing context. To address the research questions, various contributions were proposed: a flexible Industry 4.0 predictive maintenance architecture that facilitates the modular integration of complex systems, diverse data sources, advanced capabilities for better maintenance decision support; a modular predictive maintenance model using hybrid deep learning approach supporting predictive RUL model for complex manufacturing; and predictive maintenance scheduling for multiple machines components for complex manufacturing. Using the industrial cases, the proposed solutions were verified using known methods. The results of the evaluation and comparison analysis were reported in each chapter (i.e. 5, 6, 7) respectively.

The following sections will map the results to the research questions as formulated in Section 8.1. In addition, Section 8.2 will discuss the contributions as a whole. Lastly, the limitations, future work and a conclusion will be provided in Section 8.3.

8.1 Reflection of the Research Questions

Based upon the challenges in the field of predictive maintenance as discussed in Section 1.1 including the related work (i.e.,chapter 2) and case study (i.e.,chapter 3), the opportunity for providing predictive maintenance was clearly established. Subsequently, the primary research question and sub-questions were formed, assisted by the research focus in Figure 1.3, were formed. In answering the research questions, major contribution works as presented in Chapter 5, 6, and 7 were made. We reflect on the primary research question and its sub-questions in respect to the research works that have been done.

Sub-question – 1

How can predictive maintenance, and the relevant data collection, be integrated into an overall manufacturing process architecture?

To answer this question, based upon RAMI 4.0 and FIWARE, Section 5.3 provides a flexible Industry 4.0 Predictive Maintenance Architecture Platform *(PMMI 4.0)* that addresses the integration of predictive maintenance in the broader manufacturing process architecture.

In particular, *(PMMI 4.0)* supports key features such as interoperability, modularity, advanced capability, collaboration, by allowing the flexible integration of different systems or machines at different levels i.e. system, machine, component, process. The advanced capability of PMMI 4.0 includes big data analytics and the embedded maintenance services including predictive maintenance model, maintenance schedule can be operated in the collaborative manufacturing network.

In the industrial case, PMMI 4.0 is proven to be effective as a flexible Industry 4.0 predictive maintenance architecture platform. It incorporates advanced maintenance capabilities such as big data analytics, predictive models, maintenance scheduling and monitoring and complies with Industry 4.0 standards (See Section 5.4.1).

PMMI 4.0 enhances predictive maintenance by being focused on Industry 4.0. In particular, PMMI 4.0 supports flexibility, interoperability, modularity and advanced capabilities utilizing big data analytics, enabling predictive maintenance services (See Section 5.4.2).

The comparison analysis with other work confirmed the advantages of PMMI 4.0 in support of different levels i.e., machines, components, process, collaborative process of interoperability, flexibility of integration, and advanced capabilities such big data analytics, predictive maintenance services, required for predictive maintenance of complex Industry 4.0 manufacturing (See Section 5.4.3).

Sub-question – 2

How can individual machine remaining useful life be predicted based upon relevant considerations? What considerations are relevant for remaining useful life (RUL) determination?

The answer to this question, Section 6.3 provides a Modular Predictive Maintenance Model using Hybrid Deep Learning Approach (MPMMHDLA) that addresses remaining useful life prediction for multiple machines/components operating in a factory product line. MPMMHDLA is based on a hybrid deep learning which handles high sequence sensor data, and supports modular predictive model, facilitating the flexibility in dealing with multiple machine components and needs of Industry 4.0 in a dynamic fashion.

In relation to the relevant considerations, Section 6.2 provides key considerations such as state-of-the-art technique is required as traditional methods in dealing with high frequency sensor data, multiple machines/components, and dynamic needs of Industry 4.0 predictive maintenance. Particularly, remaining useful life estimation utilizing state-of-art approach such as deep learning is effective dealing with sensor/time-series data collected from factory machines operation. Complex manufacturing involves multiple machines/components generating large amount of data that requires constant update i.e., model tuning, or business needs based on new dataset that is increasingly available.

In the results, MPMMHDLA enhances existing approaches by being focussed on Industry 4.0, and has advantage, higher accuracy and lower RMSE score at over 19% than the comparative methods in the experiment context (See Section 6.4.2). A further experiment using public dataset has confirmed these initial results, proving to be more accurate, lower RMSE score at over 24% as compared to existing approaches in the experiment context (See Section 6.4.2).

Sub-question – 3

How can predictive maintenance planning be done based upon relevant factors? What factors are relevant for predictive maintenance scheduling?

The answer to this question, Section 7.2 provides *Predictive Maintenance Scheduling for Industry 4.0 Multiple Machines and Components (PMS4MMC)* that addresses data-driven predictive maintenance scheduling for multiple machines/components operating in a manufacturing product line, considering key aspects such as multiple machines/components, maintenance resource and cost in Industry 4.0 context.

PMS4MMC supports dynamic predictive maintenance scheduling that allows the flexibility in which maintenance scheduling can be created by flexible input choices. PMS4MMC supports prescriptive maintenance by enabling the support of capabilities such as flexible maintenance choices based on minimal impact of cost or downtime.

The answer to the relevant factors, Section 7.1.2 provides the key factors considered for optimal predictive maintenance scheduling in the context of Industry 4.0. The key factors include data-driven maintenance, multiple machine components, the aspect of maintenance task, cost, as well as the availability of resource such as availability status of each components, engineer.

In the industrial cases, PMS4MMC supports multiple machines/components involved in factory operation (See Section 7.3). In the experiment cases, PMS4MMC can achieve up to 30% for optimal cost, and 17% for minimal downtime impact (See Section 7.3.1).

In the comparison analysis with existing approaches, PMS4MMC has the clear advantage in: supporting multiple machines/components, predictive model driven, and support of prescriptive and dynamic maintenance in the context of Industry 4.0 (See Section 7.3.4).

Primary Question

How can predictive maintenance as a service be provided in an Industry 4.0 context?

Chapter 5 provides a flexible predictive maintenance for Industry 4.0, PMMI 4.0 which is based on RAMI 4.0 and FIWARE, providing a simplified architecture of complex systems and supporting flexible integration of different systems, machines and processes required for predictive maintenance services in a modular fashion. For the embedded predictive maintenance services, Chapter 6 provides the modular predictive model, MPMMHDLA which supports predictive maintenance RUL model utilizing hybrid deep learning approach, and Chapter 7 provides data-driven predictive maintenance scheduling, PMS4MMC for supporting multiple machines components utilizing dynamic knowledge of complex manufacturing.

In the industrial case, Section 7.3.2 provides the verification of PMMI 4.0 with the embedded MPMMHDLA and PMS4MMC as service provider within collaborative manufacturing network. The modularity and interoperability of PMMI 4.0 architecture platform offers flexible and modular components for optimized maintenance services. The optimized predictive maintenance services can be integrated using a modular fashion into FIWARE framework and maintenance schedule plans can be created by accessing distributed data in the collaborative network. IDS is adopted on PMMI 4.0 for shared data and API communication, enabling transparency and traceability.

In the industrial case (See Section 7.3.2) and comparison analysis (See Section 7.3.4), the proposed solution provides the verification and wider application in the context of collaborative manufacturing network. PMMI 4.0 predictive maintenance service enabled by MPMMHDLA and PMS4MMC can offer prescriptive maintenance as service at minimal cost impact at 12%, minimal downtime impact at 10% in the case to the manufacturing network.

Overall, based upon the results of verification, evaluation and comparison analysis (See Section 5.4, Section 6.4.2, Section 7.3), the proposed solution *PMMI 4.0* embedded with

MPMMHDLA and *PMS4MMC* is proven to be effective in supporting dynamic and flexible way of facilitating predictive maintenance as a service for business needs of real work industrial complex manufacturing, supporting modularity, interoperability and complying with Industry 4.0 standards.

8.2 Contributions

Through answering the research questions, several contributions were made as below.

1. **Predictive Maintenance for Industry (PMMI) 4.0** A *flexible architecture platform for Industry 4.0 Predictive maintenance, PMMI 4.0* was created to be a flexible architecture platform that can support simplified architecture of the industry operations, partners, communication, and the underlying technologies, applying the RAMI 4.0 and FIWARE framework. The complex interactions of industry systems, machine equipment tools, processes including collaborative partners, involve a variety of different range of applications, systems, machines, and processes requiring different interaction schemes and mechanisms. Section 5.2 provides the key components and processes of predictive maintenance, which are then applied in the proposed flexible architecture, PMMI 4.0 (See Section 5.3).

   The detailed contributions can be listed as follows:

   - A flexible Predictive Maintenance Model for Industry (PMMI) 4.0 Architecture based on RAMI 4.0 and FIWARE –Chapter 5 and Paper 1, 2, 4, Journal 1, 3, addressing key issues such as modularity, interoperability identified in the industrial case in Chapter 3 and related work in Chapter 2.
     – Flexible Industry 4.0 Predictive Maintenance Architecture Platform
     – Simplified architecture of complex systems, processes, etc. involved in Industry 4.0 based on RAMI 4.0 and FIWARE
     – Supporting interoperability and modular predictive maintenance services
     – Complying Industry 4.0 standards
   - A detailed Predictive Maintenance Process and Predictive Maintenance Model for Industry 4.0 (See Section 5.2)

2. **Modular Predictive Model**

   A Modular Predictive Maintenance Model using Hybrid Deep Learning Approach (MPMMHDLA) that supports predictive maintenance for RUL model based on data-driven approach, considering the multiple machines/components involved in the context of Industry 4.0 as well as a flexible way that facilitates managing the predictive model in a dynamic modular manner. MPMMHDLA support a modular approach in dealing with complex systems i.e. multiple machines/components and dynamic nature of Industry 4.0 (See Section 6.3). It allows the ability to input different model configurations/parameters or new dataset for the optimization of the predictive maintenance RUL model in a dynamic and modular manner.

The proposed method is compared with some widely reported related works with the same dataset and performance measurement. In all cases, MPMMHDLA offers consistent advantage and results as reported in Section 6.4.2 and subsequent publications including Journal 1 and Paper 2 were made.

The detailed contributions can be listed as follows:

- Modular Predictive Maintenance Model using Hybrid Deep Learning Approach (MPMMHDLA) –Chapter 6 and Paper 2, Journal 1, supporting modular model and hybrid deep learning approach.
  - A hybrid deep learning approach for predictive maintenance RUL model
  - Modular model facilitating dynamic requirements
  - Method embedded into FIWARE enabler
- Using MPMMHDLA, Design and Implement a new predictive maintenance model for FIRST manufacturing case, applying PMMI 4.0

3. **Data-driven Predictive Maintenance Schedule for Industry 4.0** A *Predictive Maintenance Schedule for Multiple Machines and Components (PMS4MMC)* that supports predictive maintenance scheduling for multiple machines/components involved in the Industry 4.0 environment, considering different key factors such as data-driven maintenance i.e., predictive models such as RUL, multiple machine components, the different maintenance aspect such as tasks, maintenance cost, as well as the availability of resource such as availability status of each components, engineer, in Chapter 7. For an effective predictive maintenance, an optimal schedule plan can be produced based on the considered key factors, particularly for Industry 4.0 predictive maintenance.

   - Predictive Maintenance Schedule for Multiple Machines and Components (PMS4MMC) in Section 7.2
     - Data-driven predictive maintenance scheduling considering the context of Industry 4.0 and identified key factors

  - Optimized with grouping, resource enabling prescriptive maintenance
  - Modular model facilitating dynamic and flexible method for facilitating business needs
  - Method embedded into FIWARE enabler

- Key factors considered for Industry 4.0 Predictive Maintenance Scheduling (See Section 7.1.2)
- Using PMS4MMC, Design and Implement a new predictive maintenance scheduling for FIRST industrial cases including Flexible Manufacturing and Virtual Factory, applying PMMI 4.0 (See Section 7.3)
- Supporting prescriptive maintenance for maintenance decision making whereas the results of the predictive maintenance scheduling are presented in prescriptive options (See Section 7.3.1 and Section 7.3.2).

4. **Modular Predictive Maintenance**

   Based upon FIWARE and RAMI 4.0, PMMI 4.0 architecture platform is created, enabling capabilities including modularity, interoperability in different levels' data, services, and processes including big data analysis, as well as integrate data from the lower level such as the sensors in the factory floor and data from a high level, from example, an ERP system, complying with Industry 4.0 standards. The FIWARE context broker also facilitates to plug new hardware or software to integrate existing data, services, and processes (See Chapter 5).

   The detailed contributions can be listed as follows:

   - Implementation of Advanced Analytics Capabilities/Modules/Enablers in FIWARE for PMMI 4.0 (See Chapter 5) –MPMMHDLA (See Chapter 6), PMS4MMC (See Chapter 7) and related works published in Paper 2, 3, Journal 1, 3.
     - FIWARE enabled PMMI 4.0 architecture platform utilizing GE components such as big data analysis
     - Design the methods MPMMHDLA and PMS4MMC embedded into FIWARE
     - Modular model facilitating dynamic and flexible method for facilitating business needs
   - Design a new Industry 4.0 predictive maintenance platform for FIRST manufacturing case, applying PMMI 4.0

5. Additional contribution was made whilst answering the research questions as below.

   An approach that supports *dynamic and prescriptive maintenance* is delivered by the support of capability such as flexible maintenance choices based on minimal impact of cost, downtime i.e. results of different scenario cases (See Section 7.3). The dynamic maintenance is supported by both *MPMMHDLA* (See Section 6.3 and *PMS4MMC* (See Section 7.2.3.

8.3 Limitations and Future Work

As the Industry 4.0 focusing manufacturing is complex, limitations were encountered and recognized, especially due to the time frame in which the work was to be accomplished. The limitations and further improvements, and optimizations of *PMMI 4.0, MPMMHDLA and PMS4MMC* remain as our future work that is described as below:

- ***Dataset, data fusion and automation:*** in the context of predictive models such as RUL estimation, traditional approaches such as model based, experience based, cannot meet the demands of Industry 4.0 focusing manufacturing. Thus, a data-driven *Modular Predictive Maintenance Model using Hybrid Deep Learning Approach (MPMMHDLA)* was proposed and presented in Chapter 6. At this stage, only the available sample dataset from the industrial case was utilized for the current model and the results were consistent, especially the machine is close to a failure (See Section 6.4.2 in Chapter 6).

  Improvements of *MPMMHDLA* are considered as below:

  – *Improvement of MPMMHDLA with further FIWARE enabled capabilities embedded into PMMI 4.0:* further work on model and performance tunings will be carried out. This includes acquiring new dataset e.g. sensor data operation of robots, different methods i.e. different network layers/settings for the optimization of the predictive maintenance RUL model. In this way, the wider support of MPMMHDLA will be achieved, enabling the optimization of the predictive maintenance model as well as maintenance process for the application case. Using the optimized model, different scenarios (i.e. frequency/level/type/constraint) of maintenance in the application case as well as other use cases across industries will be carried out.

  – *Data fusion and transformer learning* (Raffel et al., 2019) will be explored for improvement to MPMMHDLA. Ideally, a way of automation learning which can be integrated with our modular and hybrid MPMMHDLA model is considered.

Additional failure detections/condition monitoring based on business maintenance needs can be further investigated for enhancing the predictive capabilities of MPMMHDLA embedded into *PMMI 4.0*.

- ***Real time, continuous, automation of predictive maintenance:*** Industry 4.0 manufacturing such as the flexible manufacturing case 3.1 operates with several automated machines/tools i.e. cyber physical systems, manufacturing cell, robots, smart devices.

  Due to the scope of this work and time frame, we only completed the initial design of the maintenance process and do not address the application case for real-time, continuous and automation of predictive maintenance. We presented the initial maintenance process (i.e. automation) as part of the maintenance monitoring in Section 5.2.3.2 in Chapter 5. This process incorporating with the proposed predictive RUL model i.e. *MPMMHDLA* in Section 6and maintenance scheduling i.e. *PMS4MMC* in Section 7 need further work, and subsequent improvements can be made over the current work as below:

  – *Dynamic intelligent maintenance*, an extension of PMS4MMC will be investigated as to support the capability of dynamic maintenance i.e. self-maintenance or automation of prediction and scheduling optimization for complex equipment tools, especially in the context of the flexible manufacturing which operates with robots.

    For this case, the flexible manufacturing case (i.e. Section 3.1) will be considered since it operates with three robots, with minimal intervention from factory staff such as operator. Acquiring the operation dataset of the robots for predictive model and maintenance case, our solution can further be improved and applied. In this way, dynamic and automated maintenance may well be delivered, facilitating the orchestration of managing each predicted failure and maintenance scheduling by each robot itself utilizing advanced techniques such as deep reinforcement learning.

    The work will further extend the optimizations of related algorithms or processes applying big data analytics, leading to an advanced dynamic intelligent maintenance.

- ***Additional FIRST industrial cases analysis:*** In the scope of this work, we only used two different scenarios derived from the maintenance data. At this stage, it worked well based on the results (See Section 6.4.2, Section 7.3.1 and Section 7.3.2).

It should be recognized that the field of Industry 4.0 manufacturing, domain knowledge and available datasets are complex and hence there are various constraints. These constraints may include the several sophisticated structures i.e. dependencies, configurations, and processes of different machine equipment tools (not just one organization but also multiple organizations), variety of factory operation and production.

In addition to the cases used in this work, further *scenarios* that consider a combination of high frequency of maintenance data, different resource constraints, more detail maintenance task such as specific maintenance type of high cost, specific machine type with multiple components, etc. will be studied for improvements. This will lead to having the opportunity for the optimization of the proposed *PMMI 4.0* with the embedded *MPMMHDLA* and *PMS4MMC*.

For future work, utilizing advanced technique such as reinforcement learning based optimization is considered for the optimization of the algorithms. Subsequently, further verification of the maintenance schedule process as well as performance tuning will be gained.

- ***Further Industry 4.0 industrial cases, platforms:*** In the context of predictive maintenance for Industry 4.0, the aspect of flexibility and modular platform is essential to operating complex and dynamic Industry 4.0 systems.

  Based on the challenges and relevant requirements, PMMI 4.0 is proposed providing a flexible predictive maintenance architecture platform. The results of the evaluation and analysis showed that PMMI 4.0 met the requirements of the industrial cases, achieving high interoperability, and modular capabilities. This leads to the flexible integration of the embedded predictive maintenance services such as MPMMHDLA, PMS4MMC into existing systems and processes upon different needs.

  On the other hand, FIWARE implementation uses the core context broker which is based on event-driven approach. Challenges such as complexity, security risks should appropriately be managed. To manage the aspect of security, FIWARE generic enablers such as Keyrock, Wilma or third-party tools should be considered as required. Future research will also investigate *PMMI 4.0*'s ability to induce new types of cybersecurity for complex Industry 4.0 manufacturing systems.

  This work focused on Industry 4.0 complex manufacturing. The proposed PMMI 4.0 was verified using FIRST manufacturing cases. Since big data analytic is one key asset to organizations (Porter and Heppelmann, 2014; Zezulka et al., 2016), PMMI 4.0 with the embedded MPMMHDLA and PMS4MMC may well be applied to other industries for maintenance services since PMMI 4.0 supports the capability of big data analytics enabled predictive maintenance as well as flexible integration in a modular manner.

For instance, a data centre company may implement the proposed solution. Using the operation/condition sensor data of hard drive systems, predictive maintenance model such as RUL can be built, deployed, and configured for maintenance services. Using the big data analytics and predictive maintenance services such as RUL, maintenance analysis can be performed, enabling optimal predictive maintenance schedule can appropriately be produced.

Similar adoptions may well be applied to other industries such as smart factories, cities, buildings e.g. electricity station or traffic light with sensor monitoring and maintenance purposes. Using similar or different case, further validation of PMMI 4.0 may be gained by using the offers of commercial platforms such as Azure, Amazon.

Further improvements, and optimizations of *PMMI 4.0, MPMMHDLA and PMS4MMC* remain as our future work that is described as below:

- ***Augmentation of prescriptive maintenance:*** the current results (See Section 6.4 and Section 7.3) offers the predictive maintenance model i.e. hybrid and modular model, and scheduling i.e., different optimal results e.g. minimal cost or downtime based on input choice, in a dynamic and prescriptive way. Current solution can be further improved by exploring other techniques such as deep re-enforcement learning, etc., which will adapt and produce an optimal model when update i.e., new data, resource, etc., is made.

- ***Prescriptive maintenance as a service:*** the considered industrial cases include virtual factories or complex collaborative network organizations whereas predictive maintenance services are monetized and offered. Further work will investigate the utilization of PMMI 4.0 architecture platform which already considers international dataspace (IDS) connector for transparency data exchange, access, and control.

  Additional evaluation with various industrial cases involving different factories, experts i.e., engineers who can participate in the network by providing their specialized skills as a service or a factory with predictive maintenance capability offers its service to the Industry 4.0 manufacturing networks. Initial work regarding virtual factory was already published (Sang et al., 2021*b*).

  Further cases with optimized models will be investigated. Initial work of *Journal 3* on Industry 4.0 Collaborative Manufacturing Networks is done as illustrated in Figure 8.1, and it is pending submission process.

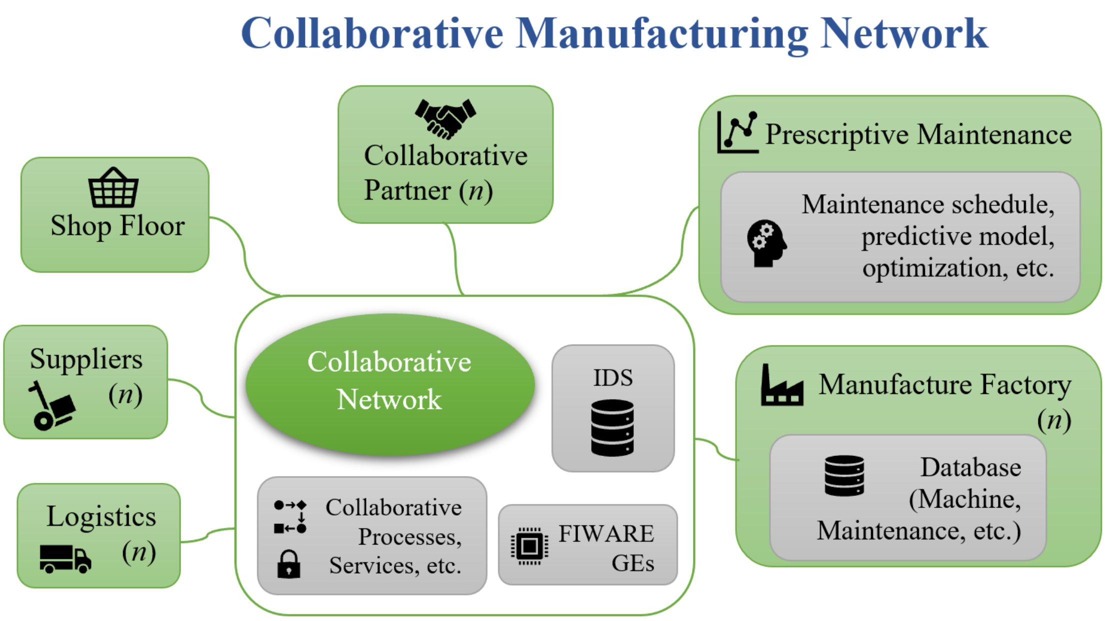


Fig. 8.1 Collaborative Manufacturing Network with Industry 4.0 Prescriptive Maintenance as a service provider

In conclusion, the research work was driven by the challenges in the field of predictive maintenance for complex manufacturing in both the academic and industry. There are several approaches introduced into industry that they are built for traditional cases or approaches which cannot meet the demands of dynamic and complex Industry 4.0 predictive maintenance.

A flexible predictive maintenance for Industry 4.0, *PMMI 4.0* embedded modular predictive model, *MPMMHDLA* and maintenance scheduling for multiple machines components, *PMS4MMC* was thus proposed, that supports flexibility, interoperability, compliance with Industry 4.0 standards, with a focus on assisting the maintenance operator or engineer in their decision making in a dynamic and modular manner, for potential failure of machines/components operated in complex manufacturing environment. This leads to facilitating modular predictive maintenance as a service, reducing downtime and associated maintenance cost whilst maintaining optimal operation and condition of the factory machine equipment tools in the context of Industry 4.0.

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