Artificial Intelligence to support collaboration in the industrial equipment life cycle

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Abstract. This paper explores the potential of artificial intelligence (AI) to support collaboration in the industrial equipment life cycle. The industrial equipment industry involves complex multidisciplinary collaboration with suppliers and customers across many machinery life cycle stages, including design, manufacturing, use and end-of-life. This paper conceptualises a set of AI-enabled digital solutions within the AIDEAS European project scope. With a case study of an industrial equipment company, we illustrate how AI solutions can be used to support collaboration in the supply chain across machinery life cycles.

Keywords: Artificial Intelligence, Collaboration, Industrial Equipment, Life Cycle.

1 Introduction

Increasing consumption and economic globalisation have forced companies to improve production processes through Industry 4.0 (I4.0) technologies, such as Artificial Intelligence (AI), Big Data Analytics (BDA), Block Chain (BC), Cloud Systems (CS), Cyber-Physical Systems (CPS), Internet of Things (IoT), Additive Manufacturing (AM) and Digital Twins (DTs). Thanks to these technologies, it has been possible to optimise and improve production processes. Moreover, I4.0 technologies are considered by [1] as enabling increased collaboration between companies. To this end, companies are exploring novel approaches to collect data throughout the production chain to optimise industrial processes, which leads to a digitisation and optimisation trend in industry [2]. Introducing new technologies offers the possibility of sharing different resources across information systems by facilitating the integration of different solutions throughout a product's life cycle. Thanks to this infrastructure, the interaction between different companies is facilitated by increasing collaboration along the production chain and a machine's life cycle.

The following sections introduce the AIDEAS project [3] on which this paper is based, and whose main aim is to develop AI technologies that can support the entire life cycle of industrial equipment. The primary goal of this project is to develop and use these technologies as a strategic tool to enhance collaboration among supply chain partners, achieve sustainability principles in the network, increase collaborative partners' agility, and promote collaborative enterprises' resilience. The project particularly focuses on machinery manufacturing companies in the European Union (EU).

The objective of the paper is to conceptualise a set of AI-based tools to deal with the collaborative perspective in each product life cycle (PLC), including design, manufacturing, use and disposal, by considering the circular economy (CE) perspective.

To fulfil the indicated objective, the paper is organised as follows: Section 2 caries out a state of the art following a four-scope approach that addresses the interconnections between collaborative networks (CNs), PLC, I4.0 and CE. Section 3 conceptualises the AIDEAS AI-based solutions, to be implemented into the four different PLC phases. Section 4 presents a case study in a food inspection industrial equipment company, in which the conceptualised AI tools considered in its business processes. Finally, discussion appears in the conclusions section.

2 State of the Art

Integrating AI into manufacturing has become increasingly vital for reducing the complexity of managing manufacturing processes. As researchers continue to explore new ways to improve efficiency in the manufacturing phase, I4.0 has emerged as a response to integrate advanced technologies like AI, Robots, IoT, and Cloud Computing by enhancing the resilience and sustainability of production systems [4]. Smart factories are an example of this integration, which employs context-aware applications and self-regulating mechanisms to optimise production processes [5]. The significance of innovation and digitisation in products, services and processes has highlighted the need to adopt advanced AI technologies in manufacturing processes. Among the various subclasses of AI, one that stands out prominently in this context is Machine Learning (ML), which has emerged as one of the most extensively employed techniques [6]. These algorithms are proven essential tools for handling high-dimensional problems and data, which are constant characteristics of CN. By focusing on computer science and engineering, AI offers several benefits in industrial sectors, including greater innovation, process optimisation, resource optimisation and improved quality [7]. It is noteworthy that these benefits have revolutionised the PLC by enabling the optimisation of processes and resources, and improving quality in all stages, from design and manufacture to removal and disposal, and at all the levels of supply chain stakeholders.

This state of the art section explores the literature from a four scope approach: (i) PLC; (ii) CE, (iii) supply chain collaboration; and (iv) I4.0 technologies. This section elucidates how these four concepts can foster a synergistic effect, culminating in a robust framework for promoting sustainable and efficient practices:

- The PLC refers to the different stages that a product goes through from creation to disposal. A product's life cycle comprises four main phases: (i) beginning of life, which includes the design of a product; (ii) middle of life, which involves the resource, manufacturing and distribution of a product; (iii) use of life, which entails a product being used and after-sales support for customers; (iv) end-of-life, which includes a product's retirement and disposal. Each phase has unique activities and goals that are important to understand by all the supply chain partners to effectively manage the product, from the product's design to its disposal [8].

- Emergent framing around waste and resource management has gained momentum in response to the intrinsic limit of sustainability that affects the modern world. It is known as CE. This framing seeks to provide an alternative to prevalent linear take-make-dispose practices perpetuated by current business models to prioritise continuous production, consumption and disposal to stay competitive [9]. CE promotes the waste and resource cycling notion to address the existing model's limits and weaknesses, a concern that has been voiced for two decades.
- CNs are acknowledged as a key facilitator in the evolution towards CE in supply chains [10]. CNs also play a crucial role in integrating I4.0, including AI. According to the I4.0 vision, smart manufacturing enterprises are organised into multiple layers of networked and collaborative subsystems. Each layer becomes a CN of smart components with increasing levels of intelligence and autonomy. The interactions between these layers lead to an exchange among smart production units, smart logistics, smart products, smart organisational and engineering units, and people. Collaboration between these entities is a requirement to support agile and resilient processes [11] [12]. According to [13], integrating collaboration into business processes, practices and standards is necessary to shift from the unsustainable linear economic system to a more sustainable circular system. Thus collaboration is crucial for harnessing the potential benefits of CE and I4.0, which are the two prominent industrial patterns in recent times. Their combined implementation into an industrial setting can enhance supply chain efficiency and competitiveness [14].
- The promising scope of AI techniques has led to them being implemented in different PLC phases. Wang et al. [15] provide an example of a framework that classifies the different AI applications and how they can be translated into different life cycle phases. To the best of our knowledge, there is no work in the literature that addresses the four-scope approach in which AI technology supports the different PLC phases by considering the collaborative perspective of supply chain partners in all the phases, from design to disposal, including the circularity concept.

In a highly globalised world, with the emergence of new players, it is crucial that the EU continues to explore disruptive ways to improve its ecosystem and maintain its position as the world's leading producer and exporter of machine tools. The EU's technological edge in the industrial equipment sector is threatened by China's rapid growth. China has launched strategic plans such as "Made in China 2025" to modernise its industrial capabilities and impact on the competitive landscape. Whilst EU has highlighted the need, according to the current Horizon Europe framework programme, for digitalising manufacturing enterprises in the scope of the industrial equipment life, especially in SMEs.

3 Industrial equipment life cycle supported by AI

One of the challenges that CNs face is to develop solutions that test, analyse and then decide about the designs that affect the entire PLC. At this point, engineers involved at the different PLC points face the need to better understand all the stages that their product goes through during its whole life cycle, and relevant information or data. Consequently, they have to handle a large amount of reliable information that will require different technological solutions being used. At this point, by properly integrating various AI tools, synergies can be achieved across all factory functions, which will ultimately have a positive impact on productivity, quality, costs, sustainability, and much more. To obtain these benefits, it is crucial to carefully select the right AI techniques and technologies for each PLC stage [16].

This section conceptualises of the main AI tools in each phase. Each AI tool works as a platform to support the design, manufacturing, use and recycle phases of the PLC by enabling the connection of data and information among the involved supply chain partners. Each AI tool will be designed to facilitate information exchange and can, therefore, improve the collaboration of all the stakeholders who participate in the PLC, including designers, manufacturers, suppliers, customers and service providers.

3.1 AI in the design phase

In order to achieve an optimal design that meets market needs and engineering requirements, a continuous problem description and solution development process is necessary. The knowledge produced in each design process stage can be captured using computational support tools, which can also help with decision making. To be more effective, designers must have access to more support tools throughout early conceptual design phases because these stages might make it difficult for them to process, arrange and represent design data [17]. Therefore, in the design phase, three AI-based tools are conceptualised, and each one is explained below:

- Machine Design Optimiser (MDO). An AI-powered tool for optimising dynamic machines and their components. The AI assistant adjusts the model parameters based on users' objective functions while considering manufacturing and operational limitations, boundary conditions and target criteria. It also analyses the impact of design parameters on machine evolution during its life cycle
- Machine Synthetic Data Generator (MDG). It synthesises high-quality datasets by simulations to train the optimisation modules in MDO. This tool allows designers to generate realistic machine design simulations and to evaluate performance in different scenarios by making AI solutions accessible for small-scale and short-term projects
- CAx Addon. An interoperability mechanism to integrate AI-assisted optimisation modules (MDO and MDG) with current CAD/CAM/CAE systems. APIs and UIs combine each optimisation module's unique functionality while also considering the needs of other common CAx solutions designers to employ AI-powered tools like MDO and MDG to enhance machine efficiency and to improve industrial equipment designs in the design phase

3.2 AI in the manufacturing phase

AI has the huge potential to contribute significantly to several aspects of the manufacturing phase. One key area where AI can help is to optimise inventory management, to reduce production and setup times, and to improve storage and delivery. The complexity of optimally performing this type of activity lies in the vast amount of data that must be handled because industrial equipment and bill of materials are huge. AI can analyse large amounts of data to predict future demand, adjust inventory levels and minimise waste and, thus, reduces costs. AI can also optimise warehouses and logistics to ensure that products are efficiently stored and delivered on time. By leveraging AI technologies, manufacturers can significantly improve efficiency, profitability and customer satisfaction, which all lead to better business performance and growth. Although there are publications on AI applications for defect prediction or maintenance diagnostic purposes, more work that focuses on AI in industrial equipment manufacturing needs to be done. Therefore, this section conceptualises three tools to cover the main processes of the manufacturing phase.

- Procurement Optimiser Toolkit (PO). It is an AI solution that helps manufacturers to optimise materials inventory and purchasing while considering customer lead times. PO reduces inventory costs and the risk of stockouts with advanced algorithms that forecast demand, recommend reorder points, and suggest cost-effective or available alternatives
- Fabrication Optimiser Toolkit (FO). It is an AI solution that predicts production and setup times, dependences, and other factors that influence production scheduling and resource allocation. This enables manufacturers to respond quickly to changing conditions and make informed decisions about resource allocation, reducing downtime and increasing productivity. FO optimises manufacturing processes, reduces waste, and improves quality and competitiveness
- Delivery Optimiser Toolkit (DO). It is an advanced solution that optimises product storage, transportation, logistics scheduling and planning. DO leverages AI to deliver the most efficient solutions possible by reducing transportation costs, increasing delivery speed and improving customer satisfaction. It also identifies and resolves bottlenecks in the supply chain, which improves efficiency

3.3 AI in the use phase

In this stage, the product is in the hands of the end customer and/or some service providers, e.g., maintenance. The history of the product about conditions of use, failures and maintenance can be collected to create an up-to-date report on the product's condition. Industrial equipment involves devices designed for tasks in industrial environments. They are robust, durable, efficient and productive, and employ advanced technology to improve their performance. Their smooth operation in the use phase ensures that quality goods or services are produced.

AI solutions, such as quality monitoring and machine vision, detect defects in real time and reduce the number of defective products, while ML algorithms and predictive maintenance prevent failures and defects in production. The Zero Defects philosophy and AI solutions aim to improve product quality and increase production profitability [18]. Integrating these solutions into a factory's daily operation improves its competitive market position.

- Machine Calibrator Toolkit (MC). It uses AI to calibrate industrial equipment efficiently by reducing time and costs. It can also improve accuracy and precision to meet required specifications
- Condition Evaluator Toolkit (CE). It employs advanced algorithms to determine the condition of machines, to identify potential problems before they become critical, and to optimise maintenance schedules
- Anomaly Detector Toolkit (AD). It resorts to ML to detect component- or machine-level anomalies by enabling manufacturers to take corrective action before problems become critical
- Adaptive Controller Toolkit (AC). It trains machine controllers to perform optimally and to adapt to changing conditions in real time by reducing the risk of unplanned downtime and improving efficiency
- Quality Assurance Toolkit (QA). It applies AI to monitor the quality of manufactured products by identifying potential problems before the product is delivered to the customer and reducing the risk of returns and warranty claims

3.4 AI in the repair-reuse-recycle phase

This phase is the last life cycle phase. It aims to find alternatives for machines to return to some previous phases of their life cycle, and always depends on the state of the machine. In this phase, the potential of AI-based tools is used to promote sustainability in the machine sector by extending machines' useful life, reducing waste and improving material flow efficiency.

- Prescriptive Maintenance toolkit (PM). It uses AI algorithms to predict a machine's remaining useful life and to identify necessary maintenance requirements. In this way, maintenance can be performed more accurately and costly failures that may compromise machine performance can be avoided
- Smart Retrofitter toolkit (SM). It applies AI to optimise working conditions and product quality during retrofitting. The retrofitting process involves upgrading or improving older machines to give them a second life, and to reduce the amount of generated waste. By means of this tool, customers can simultaneously obtain economic and environmental benefits
- Life Cycle toolkit (LC). It combines AI and life cycle methodologies to identify the best way to end a machine's life cycle. A multi-objective optimisation strategy balances economic, social and environmental benefits to ensure a sustainable solution
- Disassembler toolkit (DIS). It utilises AI models to optimise machine disassembly and recycling processes, which helps to reduce waste and to improve material circulation efficiency

3.5 Machine passport

Machine passport (MP) will provide an intelligent platform responsible for acquiring, managing and exchanging large-scale data from multiple sources across devices. The MP is, therefore, designed to store and share the manufacturing data collected throughout the different PLC phases, including design, manufacture, use and repair-reuse-recycle. It aims to develop protocols, standards and data exchange interfaces that facilitate the integration, sharing and exchange of intelligent and reliable data between different types of computer-aided systems and manufacturing phases. This is achieved by using an intelligent platform to acquire, manage and share large-scale manufacturing data from multiple sources, which can be visualised with a variety of devices and dashboard interfaces.

Unified standard service modelling techniques ensure data compatibility, interoperability, consistency and quality. The MP therefore ensures traceability throughout the machines' life cycle. With this information, it is possible to identify the phases when greatest distress occurs. By identifying the point at which a machine's performance declines, a plan can be drawn up to improve its design, manufacture or use based on reliable accurate information. The MP uses explainable AI algorithms to guide the orchestration of large-scale data flow and knowledge management throughout the PLC manufacturing phase. By manipulating ML knowledge, the MP facilitates decision-making processes related to the PLC by guiding optimal configuration strategies to repair, reuse and recycle industrial equipment.

Thanks to the MP, it is now possible to track the condition of machines throughout their life cycle, which makes it possible to identify the phase in which machines undergo the most stress. This information can then be used to improve practices in that stage or to anticipate potential problems in earlier stages through better designs by eliminating inefficiencies or applying alternative materials, which results in less wear and tear and a longer life cycle for machines.

4 Use case: food inspection industrial equipment company

The AIDEAS project works with four industrial scenarios, in which AIDEAS solutions are conceptualised. As each of the industrial pilots involve equipment manufacturers from different sectors, AIDEAS solutions address diverse sets of collaborative processes. The pilot used in this paper specialises in the development and production of artificial vision equipment that utilises machine vision and X-ray technologies to sort fresh fruit and vegetables, and to inspect food products. This section focuses on conceiving the AIDEAS solutions to enable the food inspection industrial equipment company to improve collaboration with supply chain stakeholders.

To define the use case of the aforementioned pilot, we ran the methodology to define use cases for the validation of European research projects Results (MUCER) [19] that consists of: (i) modelling AS-IS scenarios in each use case; (ii) redefining the business processes for each use case as TO-BE scenarios, which incorporate the AIDEAS European project solutions and show evolution from AS-IS scenarios. As the objective of this paper is to show how AIDEAS solutions can be formulated to support collaboration with supply chain partners in industrial equipment network, this paper conceptualises TO-BE scenarios of the MUCER methodology. Accordingly, the food inspection company included four different business processes in which to conceive AIDEAS solutions for boosting supplier and customer collaboration along three of the life cycle phases, which are: manufacturing, use, and repair-reuse-recycle. With the AIDEAS solutions' conceptualisation, the advances expected for the food inspection company are:

- A1. Optimise machinery manufacturing and storage processes for improved efficiency, reduced costs and increased productivity by considering suppliers' restrictions and unpredictable behaviours
- A2. Increase efficiency in managing machine deliveries to customers
- A3. Reduce machine setup times for optimal customer utilisation, which leads to zero defects of product inspection
- A4. Improve smart maintenance planning

The following sections describe the four scenarios that fulfil the listed advancements. Each scenario reflects the consideration of some previously conceptualised AIDEAS solutions. We highlight how AIDEAS tools support collaboration with supply chain partners. Finally for each scenario, we list the benefits defined by the studied use case thanks to considering the conceptualised AIDEAS solutions.

4.1 AI-based assessment for procurement and production planning in the manufacturing phase

The manufacturing phase comprises two use cases that involve the incorporation of AI technologies to deal with the procurement, manufacturing and delivery processes, which employ the PO, FO, DO solutions. In this section we deal with the PO and FO solutions, while next section 4.2 conceptualises the DO solution.

In the food inspection pilot, PO will help to optimise inventory and replenishment based on requirements from manufacturing (of components) and after sales (spare parts) and will enable the advancement A1 to be met. In addition, it will need to update procurement to deal with the uncertainty of the component lead time. FO will be applied for automating the allocation of resources and production planning based on machine type, run times, available components, bill of materials and operators. It will also recalculate production planning when components are short.

FO and PO will play a crucial role in collaboratively computing the Materials Requirement Plan (MRP) while considering the uncertainties that arise from suppliers. One of the key challenges in the MRP is the unpredictability of supplier performance, such as delays, quality issues or unexpected changes in supply chain dynamics. By leveraging AI algorithms, such as ML and predictive analytics, PO will be able to analyse the data related to supplier performance, including historical data, real-time data and external data sources, and can use this information to generate an accurate timely MRP that allows real-time feedback and input from suppliers' uncertainties.

The expected benefits obtained by considering PO and FO will be to: (i) increase resource efficiency; (ii) reduce downtime; (iii) cut the manufacturing cost; (iv) improve inventory and purchasing for both machine components and spare parts.

4.2 AI-based assessment for delivery planning in the manufacturing phase

The DO system, considered into the food inspection pilot will be used to optimise the delivery of inspection machines and to fulfil advancement A2. In this use case, the AIDEAS food inspection pilot collaborates with its customer.
The aim will be to optimise space in delivery and, therefore, inventory and transport costs. Currently, there are only two types of standard platforms that fit two types of machines with different proportions. However, these platforms should be adjusted to different machines to optimise the space occupied in both the company's working areas and transport media.

DO will be fed by customer requirements and machine specifications. This may involve understanding customer expectations regarding packaging requirements, and any special handling or storage needs. Based on the collected requirements, the parties involved in the delivery process will draw up a plan for how goods or services will be delivered, including the timeline, delivery route, and any necessary transportation and logistics arrangements.
The foreseen obtained benefits will be to: (i) improve the design of platforms to transport single and multiple machines in a standard container to optimise space; (ii) optimise the cargo transportation unit; (iii) optimise the loading of machines in a standard container. In Figure 1, the configuration process of the delivery process is represented with business process modelling notation (BPMN). It depicts the collaboration points between the manufacturer and the customer, and how the DO solution is used to support the delivery process of machines.

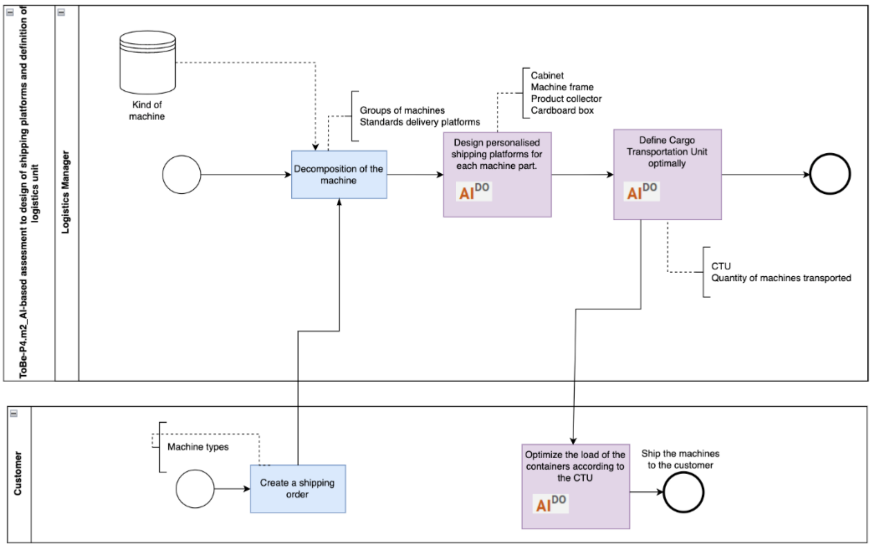

Fig. 1. BPMN: manufacturer-customer collaboration in inspection machine manufacturing

4.3 AI-based assessment for the configuration of inspection machines in the use phase

The use phase is composed of a scenario that will involve incorporating AI technologies to deal with the proper configuration of the inspection machine once it is installed at the customer site, which employs the QA solution.

In the use phase, one of the processes to be performed is the configuration of the machine, which will enable to deal with advancement A3. In this scenario, of the AIDEAS food inspection pilot, the company collaborates with its customer to provide proper machine use when it is at the customer site.

The customer will define a set of requirements for the machine to be manufactured and assembled in the food inspection machinery company. The configuration of the inspection machines starts at the manufacturer's site when the inspection machine is produced according to customer requirements and when the collection of what the manufacturer names "recipes" is programmed. Each recipe contains the configuration of the machine according of a set of characteristics of the product to be sorted (e.g., product type, its size and quality). Depending on the market, the classified product is to be delivered, so the recipe can change. For example, products classified in an inspection machine can be delivered to a very restrictive market in quality terms or to markets where quality is not so restrictive. Therefore, the recipe (machine configuration) of the inspection machine is different when the product to be sorted is delivered to a distinct market kind. Moreover, depending on the initial quality of the product to be classified, or its colour, size, etc., configuration also changes.

When the food inspection machine is classifying homogeneous products, all elements are expected to be similar in terms of size, shape, colour, texture, quality, among others. This makes the classification task easier because the process can rely on very specific and easily measurable criteria in the recipe configuration. However, when the product to be classified widely varies, such as a batch of food of different sizes, shapes, colours and textures, the classification task can be much more complicated. In this case, more accurate and flexible recipes are needed, which make the classification task more complex and require more time and resources. Therefore, it is important to consider product homogeneity when configuring the inspection machine. In this way, the appropriate recipes with accurate classification criteria must be chosen to make a precise and efficient classification.

Currently, the inspection machinery producer defines a collection of recipes that respond to different characteristics of the products to be classified. When the machine is delivered to the customer site, QA will check and monitor the entrance of the product in the machine and, according to the identified characteristics, QA will automatically propose a recipe of the inspection machine. If the product changes characteristics, QA will detect such changes and automatically proposes a new recipe or configuration on the machine. Therefore, the machine recipe will be automatically selected by QA according to the characteristics of the product to be classified and the market to where it will be delivered. In Figure 2, the configuration process of the inspection machine is represented by BPMN. The collaboration points between the manufacturer and the customer, and how the QA solution will be used, are indicated to support machine calibration for accurate recipe selection.

The benefits that will be obtained by applying QA are to: (i) reduce the inspection machine configuration time; (ii) optimise the work of the operators at the foot of the machine when a recipe is chosen to start classifying a new product without the worker having to make appropriate recipe estimation; (iii) increase accuracy during the selection recipe process.

Therefore, QA will enable to automatically select the proper machine configuration according to the type and quality of the product that enters the machine to be classified. QA will also change the machine configuration automatically when the QA hardware detects changes in the characteristics the product that enters the machine to be classified.

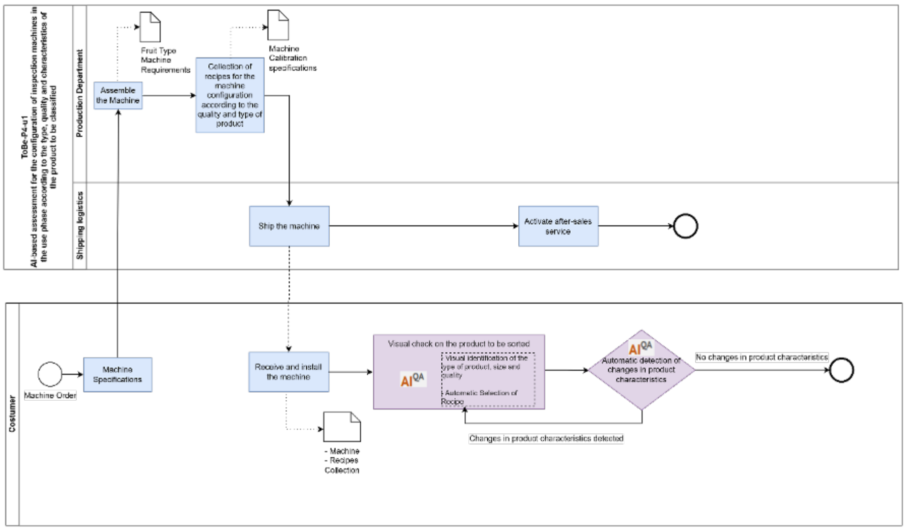

Fig. 2. BPMN: of manufacturer-customer collaboration in inspection machine configuration

4.4 AI-based assessment for predicting maintenance requirements in the inspection machine in the R3 phase

The R3 phase is composed of a use case that will involve the incorporation of AI technologies to predict maintenance actions in an inspection machine and will support its proper repair once installed at the customer site, which will use the PM solution.

R3 phase one of the process to be performed involves the repair of the inspection machine and allows to achieve advancement A4. In this use case, the AIDEAS food inspection pilot will collaborate with its customer to provide proper machine maintenance when it is at the customer site.

The PM tool will be able to predict the useful life of a component or inspection machine. It should anticipate the time when the component will be changed before product classification failures start. The critical components defined by manufacture to apply predictive maintenance include X-ray generator, straps, chains, bands or bearings. The PM will be fed by: (i) the machine's years of use at the customer site ; (ii) after-sales manager's experience; (iii) the estimated use of the component defined by the supplier; (iv) the real data of component use, which is monitored by the customer; (v) the last date when the component was changed; (vi) the last date when the component was repaired; (vii) component age; (viii) km of the machine; and (ix) hours of work per day and work rate of machines.

In Figure 3, the maintenance process of the inspection machine is represented by BPMN. The collaboration points between the manufacturer and customer, and how the PM solution will be used to support the prescriptive maintenance of machine components and ensure machines' long end-of-life is depicted.

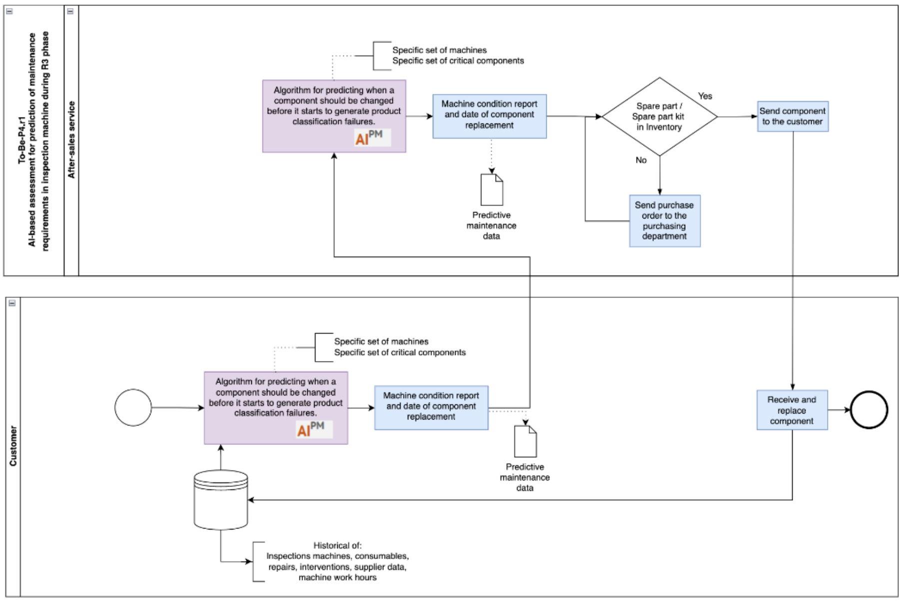

Fig. 3. BPMN: manufacturer-customer collaboration in inspection machine predictive maintenance

5 Conclusions

One of the key technologies that drives I4.0 is AI, which enables machines and systems to learn from data and to make decisions on their own. AI is transforming the way that enterprises of supply chains operate and offers the potential to optimise all the PLC phases, including design, manufacturing, use and disposal, to reduce costs, improve quality and enhance sustainability in all phases by considering a circular approach. CNs are also an important I4.0 aspect because they enable different actors in the value chain to share data, resources and knowledge. AI can enhance the effectiveness of CNs by providing real-time insights and predictions, and by enabling better decision making and coordination among network participants. The PLC, AI, and CN combination has the potential to revolutionise the way enterprises make things and create value in the future. So this paper conceptualises a set of AI tools that support all the PLC phases by enhancing collaboration among the network partners involved in each phase. When the conceptualisation phase ends, we will move on to the implementation phase of the proposed AI tools. Future implementation will involve selecting appropriate AI algorithms, preparing and cleaning data, and integrating AI tools into an infrastructure. Further, AI tools will be tested to assess the benefits of the AIDEAS project in the industrial pilots. Finally, the MP solution is still in its early stages of conceptualisation, therefore, the next steps are to identify the data whose traceability is crucial in the machine manufacturing industry. In the use case considered, MP data will contain the machine unique identification and IDs of crucial components, such as the ensembled x-ray cameras.

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