International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 / https://doi.org/10.14445/22315381/IJETT-V70I12P219

Volume 70 Issue 12, 179-193, December 2022

Original Article

Sustainable Manufacturing in Industry 4.0 Context: Theoretical Background and Multi-Agent Architecture

Nawal Bensassi[1], Maha Rezzai[1], Dachry wafaa[2,3], Hicham Medromi[1]

[1] *Laboratory of Computer System and Renewable Energy, ENSEM, Hassan 2 University, Casablanca, Morocco*
[2] *Laboratory of Engineering, Industrial Management and Innovation, FST, Hassan 1 University, Settat, Morocco*
[3] *Laboratory of Industrial Engineering, Information Processing and Logistics, Hassan 2 University, Casablanca, Morocco*

[2,3]*Corresponding Author : wafaa.dachry@uhp.ac.ma*

Received: 26 August 2022 Revised: 09 November 2022 Accepted: 24 November 2022 Published: 24 December 2022

Abstract - *Today, manufacturing companies are confronted with increasing pressure on prices, lead times and demands of product customization. They need to reinvent their business and industrial operations along the value chains for greater efficiency by exploring advanced technologies such as cyber-physical systems, artificial intelligence, robotics, the Internet of things, big data, cloud computing, etc. Under the current global scenario, the trend towards using these technologies is considered a major factor in the fourth industrial revolution (called industry 4.0). Many organizations are in the transition stage to I4.0 in order to make their processes more collaborative and smarter. Besides that, the new possibilities opened up by these technologies can also increase the efficiency of circular economy and, more specifically, sustainable manufacturing. This is to optimize resources, reduce waste generation, manage returned products, and help factories implement cleaner industrial processes. The present study considers articles focusing on environmental sustainability in the industry 4.0 context. We draw up an analysis of the theoretical background, including related works on sustainability and industry 4.0. The paper also presents sustainable reverse logistics architecture based on multi-agent and expert systems. We have combined the agent paradigm with industry 4.0 to achieve a scalable, efficient, reliable, autonomous, and adaptive system.*

Keywords - *Sustainable manufacturing, Industry 4.0, Circular economy, Reverse logistics, Multi-agent system.*

1. Introduction

In recent years, an increasingly important focus has been given to the fourth industrial revolution (called industry 4.0). This new paradigm is marked by the introduction of digital technologies into the smart manufacturing environment.

Before this, the industrial world has undergone several revolutions [1]. Chronologically at the end of the 18th century, the first industrial revolution introduced production lines and the steam engine using hydraulic energy to power the machines [103]. In the 1870s, the second revolution used electric production lines allowing higher yields than steam and lower production costs. The 20th century was marked by the production system transformation from mechanics to automation, thanks to electronics and computing. The fourth revolution primarily concerns the smart factory based on interconnected objects and data analysis [2]. Industry 4.0 emphasizes the networks of machines in an intelligent factory setting capable of autonomously exchanging information in real time and controlling each other [3].

Industry 4.0 marries production operations and physical equipment to smart technologies such as Cyber-Physical Systems, the Internet of Things, cloud computing, big data, machine learning, etc., for creating a more holistic and better-connected ecosystem.

Cyber-Physical Systems (CPS) are the combination of IT elements (software, hardware, sensing devices, computational applications) and physical entities that can interact with humans through many distinct technologies [4] [5]. In the cyber-physical environment, machines can communicate, collect real-time data, and take informed decisions [6]. CPS leads a revolution in industrial applications for the monitoring, interaction, manipulation, and control of the manufacturing environment [7]. Regarding the Internet of Things, it aims to implement network and communication protocols between connected objects. Integrating IoT devices in cyber-physical systems provides various ways of interacting and manipulating physical systems through seamless network connectivity and refined user control over the actuation side [8]. It enables real-time transmission of data for decentralized decision-making processes [9]. So, combining CPS and IOT offers innovative services in different manufacturing applications. In addition, Big data in industry 4.0 has the vast potential to help reduce malfunction rate and improve production and product quality. These tools and algorithms enable to process of a large variety of data, including capture, transfer, storage and analysis. The big data techniques are implicitly used in CPS by relating to the Internet of Things (for collecting data) and cloud computing (for storing and accessing data through the Internet). Big Data also improves system scalability, security and efficiency [10]. Several technologies have made emerged industry 4.0 concept [11]; we will review the main concepts in this paper. Most of the technologies applied within the Industry 4.0 are not necessarily new; what is recently developed is the combination of them to optimize, in our context, the sustainable environment.

The progressive exploitation of resources and increasing environmental degradation have shifted focus to sustainable issues [12;13]. Sustainability is driving companies today to think beyond economic benefit goals and move towards sustainable manufacturing processes to address environmental and societal factors. Indeed, many companies are committed to the cause of sustainability in their processes [14] to optimize resources, reduce waste generation, manage returned products and help their factories to implement cleaner industrial processes.

In this context, industry 4.0 technologies can be considered the new revolution in the supply chain, which aims to design sustainable products based on closed-loop life cycles and achieve maximum efficiency and outcome by minimum resource utilization [15].

The consideration of sustainability in supply chain management is mainly based on three factors [16]: (i) pressure from stakeholders (such as investors, non-profit organizations, profit organizations and customers) to reduce the environmental impacts that are generated (increase in waste generated, increase in pollution...); (ii) the improvement of the brand image which serves as an element of differentiation vis-à-vis competitors; and (iii) regulations which are becoming more and more restrictive.

The main objective of our research is to explore the concept of a circular value chain and discuss the sustainable impacts. In fact, circular economy solutions based on industry 4.0 technologies have been developed to transform returned products in the end-of-life (EOL) or end-of-use (EOU) into new products [17]. These returned products can be recycled, repaired, reused, refurbished and remanufactured after their disposal. However, only the remanufacturing process guarantees that the quality of remanufactured products is the same as that of new products [18]. According to [19], the circular economy becomes not an option but inevitable for continued economic prosperity and ecological balance.

Moreover, we explore using a Multi-Agent System (MAS) to implement a decentralized architecture, taking advantage of characteristics of agents, e.g., intelligence, autonomy, reasoning, cooperation, and reactivity. This system is based on various agents for performing: collecting data, processing data, storing data, making predictions and creating knowledge to facilitate making decisions processes.

To solve the industry 4.0 problems, some authors have used the multi-agent approach for data analysis and prediction. Their experimental results show that prediction with a multi-agent system was more precise than prediction based only on the data [20]. MAS are a promising approach to developing Industry 4.0 components [21]. The autonomous decision and distributed cooperation between agents lead to high flexibility in smart manufacturing [22].

In this paper, we will aim to answer the following research questions:

RQ1: What is the leading Industry 4.0 technologies used in sustainability manufacturing?

RQ2: How do I4.0 technologies and multi-agent system adoption affect sustainable manufacturing?

RQ3: How can we manage a returned product in the industry 4.0 context?

The paper comprises the following sections: Section 2 describes the fundamental concepts of our research work, we survey anterior work; Section 3 presents the architecture of our system; Section 4 concludes the work.

2. Theoretical Background

2.1. Industry 4.0

The term Industry 4.0 originates from Germany; it was first used at the Hanover Motor Show in 2011 [1]. Industrialists, experts and university researchers gathered together. They announced it to clarify their vision of industry integrated with high technology, namely terms that are becoming more and more popular such as Internet of Things, Internet of Services (IoS), Cyber-Physical Systems (CPS), Artificial Intelligence, etc., [23]. Different researchers have given different perceptions of the meaning of Industry 4.0. According to [24], Industry 4.0 is seen as business management through digitization to provide real-time market data, and operational information exchanged between machines and links in the chain logistics, production processes and customers. For [25], Industry 4.0 represents using sophisticated machines, advanced computer applications and sensors to plan, forecast, adjust and control societal outcomes and business models. Industry 4.0 is seen as an advantage for staying competitive in any industry. Thus, to create a more dynamic production flow, the optimization of the value chain must be controlled autonomously. Industry 4.0 encourages manufacturing efficiency by intelligently collecting data to make the right decisions and execute them without a doubt. By using the most advanced technologies, the procedures for collecting and interpreting data will be easier. The operational interoperability capability acts as a "connecting bridge" to provide a reliable manufacturing environment in Industry 4.0 [26]. Industry 4.0 is a strategy that builds on digital and connectivity, using different technologies to transform processes, products and services. This transformation occurs through decentralized and real-time decision-making, allowing new capacities for systems, in cooperation with humans, to go from surveillance to autonomy [27] [28].

2.2. Technologies of the 4.0 Context

Industry 4.0 is commonly used as a synonym for Cyber-Physical Systems [29]. It is defined by [30] as a set of connected cyber-physical systems capable of using and analyzing a large mass of data in the manufacturing field.

CPS corresponds to the integration of machines and processes in order to make factories capable of communicating autonomously and independently [31] [32] by setting up monitoring and control elements' operating conditions [33] [34].

According to our research, we summarize that Industry 4.0 incorporates a set of technologies based essentially on the concept of a Cyber-physical system. The following authors consider a list of eleven core Industry 4.0 technologies resulting from a literature review. These technologies will support our research framework and architecture:

2.2.1. Internet of Things (IOT)

Devices and machines connected via the Internet with a wired or wireless network, capable of taking measurements on a physical environment (sensors) and acting on it (actuators). IIoT refers to IoT technology used in the industrial domain (ajouter references). IIOT uses connected sensors and smart devices in production workshops to collect data for analysis [35] [36]. The key elements of an IIOT platform are smart devices, the communication network (Modbus / TCP, TSN etc.) and Big Data Analytics (Hadoop, Hive, Spark etc.) [37]. The architecture of IIoT is often seen as an evolution of M2M (Machine to Machine) technology [38].

2.2.2. Big Data (BDA)

In the context of Industry 4.0, data is generated by multiple sources such as sensors, machine controllers, manufacturing systems, people, etc. All this massive data (Volume), arriving at high speed in near real-time (Velocity) and different formats (Variety), is called "Big Data" [39]. The Internet of Things is considered an important data source that can lead industries to harness Big Data tools [40]. The Big data platform is based on various applications to collect, process and store data. It also offers advanced data analysis techniques (Big Data Analytics) and data interpretation tools (Visual Analytics).

2.2.3. Cloud Computing (CC)

Cloud Computing is a virtual platform based on IT services, public or private, offered by different suppliers (servers, storage, networking, services, applications). The cloud allows users to access documents/data from any location, provided they can access the network through the Internet. Cloud computing offers three services: IaaS (infrastructure as a service), PaaS (platform as a service) and SaaS (software as a service) [41]. In the context of 4.0, we talk about industrial cloud computing. The platform supports data from sensors and provides secure data sharing between machines, information systems and operators. However, due to the increasing number of accesses, the cloud can experience problems with bandwidth, latency, network downtime, etc. [42]. This is why other layers of processing and storage can be combined with the cloud layer; we speak of Fog computing and Edge computing. Fog Computing provides storage, computing and networking services, etc., near user devices (e.g., information systems, network routers). This concept is based on decentralized data processing in elements called "fog no" [30 43]. The data generated by the IIOT will then be processed first in the Fog layer before being transmitted to the cloud for other forms of processing.

Regarding Edge computing, it allows the integration of computing power and data storage into the physical environment of the IOT (machine, robot, controller, etc.). Each object has its system/application that it uses for its internal processing. In any case, whether for the Fog or the Edge, the data is processed and analyzed locally, with no need to have internet access. The company can consider combining the three concepts depending on the platform it wants to set up. The following figure shows the interaction between the different layers.

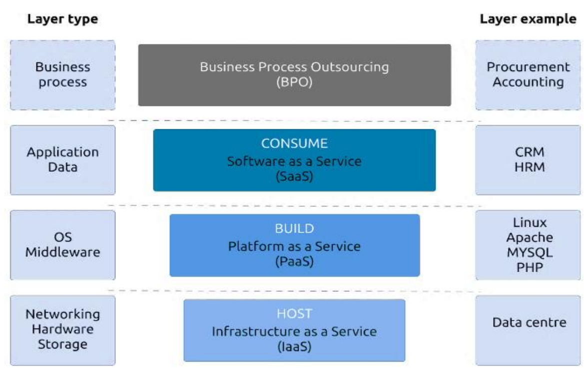

Fig. 1 Cloud computing layers (Source: www.visma.com)

Artificial intelligence (AI) is a cognitive science based on a set of theories and techniques allowing to design of systems capable of simulating intelligence and reproducing human behaviour in their reasoning activities [44]. Today we are talking about industrial artificial intelligence because AI technologies can help industrial companies improve their systems' availability, reliability, autonomy and performance quality. Industrial AI can help develop intelligent predictive systems to diagnose, forecast, predict, and help avoid or prevent breakdowns and shutdowns. AI was first developed through expert systems. This tool remains effective for performing reasoning from a knowledge base (facts and rules) fed by human experts, but today in 4.0, machine learning is used. ML uses mathematical and statistical approaches to empower industrial systems to learn from data analysis. The aim is to design systems that learn over time and by themselves, thus developing some form of intelligence and autonomy rather than reproducing predefined human decisions. Machine Learning is characterized by exploiting supervised learning algorithms, unsupervised learning, semi-supervised learning and reinforcement learning [45].

2.2.4. Data Mining (DM)

Data mining is applied to efficiently provide valuable information for management and decision-making in companies [46]. This technology consists of extracting knowledge and rules to detect new trends from a large number of fuzzy or random data (Big data). The data used generally does not have an apparent connection at first glance. Therefore, data mining analyzes these data from several angles by modeling, classifying and grouping them to identify hidden correlations better and predict future results [47]. Once trends are generated, they can help machine learning perform its functions [48]. We can then say that Data-mining refers to the practice of analyzing data, using learning techniques, from a set of data generated by other computer tools.

2.2.5. Cyber-Security (CS)

Aims to protect computer networks from accidental or malicious attacks and threats [49]. In the industrial context, traditional systems are generally closed, and security is ensured by isolation and physical access control. However, modern manufacturing machines are equipped with many smart devices connected to other machines, PLCs, data management systems (ERP, MES, CMMS, etc.) and data analysis systems. This interconnection now presents threats to the integrity of systems. According to a study conducted by the European Network and Information Security Agency (ENISA), the most critical elements in terms of cybersecurity in Industry 4.0 are control systems Industrial Control Systems (ICS Industrial Control systems), followed by Industrial Internet of Things (IIoT) gateways, sensors and actuators [50]. Indeed, security does not have absolute priority when creating IoT devices [51]. Poorly protected, this can constitute potential loopholes and endanger specific industrial applications for piloting, planning and monitoring production. Potential hacker targets seek trade secrets or financial gain through ransomware and data exfiltration. Cyber security is therefore expected to become an integral part of the strategy, design and operations of companies that adopt the Industry 4.0 paradigm.

2.2.6. Additive Manufacturing (AM)

3D printing is based on the principle of rapid and precise manufacturing of parts by accumulating successive layers [52]. The reduction in costs of 3D printers and the precision and speed of printing has encouraged the use of this technology in industries, whether to create small spare parts, complex components or prototypes. Several techniques of additive manufacturing have been explored in recent years. These techniques can be classified by the state of the material used in the printing: (i) a liquid material (e.g. molten wire deposition (FDM) modeling); stereolithography (a rapid prototyping technique (SLA), which makes it possible to manufacture solid objects from a digital model); discrete particles (usually powders, e.g. selective laser sintering (SLS)); electron beam fusion (allowing 3D printing of metal parts (EBM)); or solid sheets (manufacture of objects by rolling, for example, modeling of laminated objects (LOM)) [53]. Each of these techniques has its own strengths and weaknesses [54].

2.2.7. Robots and Cobots (RO)

Robots are widely used in industry, and they have made an irreplaceable contribution to manufacturing, assembly, transport, etc. They are known for their speed in carrying out tasks and their precision. Robotics technologies are experiencing significant development thanks to the emergence of Industry 4.0. Indeed, the next generation of robotics could play an essential role in meeting the dynamic needs of intelligent and collaborative manufacturing [55]. Robots are generally classified in the category of cyber-physical systems, and they are generally composed of: a digital controller for the execution and management of the system, physical components for the perception of the environment and the manipulation of elements that facilitate movement, cyber components for connection to the network [56]. Robots can be autonomous, mobile and collaborative "Cobots". An autonomous mobile collaborative robot can move around different locations in the factory. It is used in manufacturing workshops to improve flexibility and productivity [57]. Collaborative robots are set up to facilitate human-robot collaboration [58]; they are built in such a way that they can communicate with each other and with people, learn, educate themselves and teach human beings.

2.2.8. Digital Twin (DT)

Each product has its cyber twin, generally developed with the physical product. The digital twin can be defined as a complete digital representation of an individual product [59]. A digital twin includes the same primary characteristics as well as the behavior of the actual product through recorded information or basic models. The behavior of the actual product can be simulated using the digital twin in a provided environment. This simulation is decoupled according to the time and place of the physical product. So the primary benefit of a digital twin is the location and time-independent simulation of the behavior of an actual product.

With this new concept, experiences with actual products can be reduced; therefore, time and costs can be saved in the product development process [60]. The basic structure of cyber twins is an information model in which all relevant information and their relationship to each other is collected and described. At the end of this structural model, the sensor data is recorded and can be used in the calculations. Analyzes are continuously updated with real-time sensor data. Therefore, decisions about future behavior can be made based on reliable analyzes, calculations and simulations [61].

2.2.9. Blockchain (BC)

It is a technology applied to transactions requiring traceability and visibility. The blockchain allows users connected to the network to share information without an intermediary. In a report published in December 2018 on the uses of blockchains and other registry certification technologies, the joint information mission of the National Assembly defines blockchain as a registry. This extensive database has the particularity to be shared simultaneously with all its users. The latter can enter data into it according to specific rules set by a very well-secured computer protocol thanks to cryptography [62]. The particularity of this register is the recording of data in the form of small blocks, which can no longer be modified after validation (except by agreement between its owners). Thus, blockchain has attracted much attention in distributed technologies such as the Internet of Things, as it improves security and privacy, increases system fault tolerance, and provides faster reconciliation. , creates a scalable network and contributes to the reduction of costs and the time of removal of intermediaries [63].

2.2.10. Augmented Reality (AR)

Augment reality and virtual interface, two terms denoting a two or three-dimensional technology that increases sensory quality by adding a contextual layer of information to real data. This technology is based on methods that represent the real environment by adding virtual fictitious elements [64]. Augmented reality can provide information on all phases of a product's life cycle (product design, production processes and progress, quality control, etc.). This information is helpful for operators and hierarchical superiors to make the necessary decisions [105]. The realization of augmented reality requires the development of several technological and computer supports to limit the gap between the imaginary and the real, thus creating a convergence of images [66] [67].

2.3. Sustainable Manufacturing and Circular Economy

The increase in customer demands can cause severe damage to the environment, mainly because of industrial waste and the use of non-renewable materials. Manufacturers are now oriented towards sustainable development, changing their production patterns to shield natural resources and ecology [68]. Thus, when producing a new product, the focus should be on minimizing the entire product life cycle's adverse effects on the environment from the very early stage of material extraction towards product disposal [69]. In this context, different concepts have emerged to achieve sustainable development goals, such as "green logistics", "reverse logistics", "sustainable manufacturing", "sustainable supply chain", "circular economy", "recycling", "remanufacturing", etc.

Sustainable manufacturing can be defined as « the production of products in a way that minimizes environmental impacts and takes social responsibility for employees, the community, and consumers throughout a product's lifecycle, while achieving economic benefits » [70;71]. It can also be described as integrating different processes to produce high-quality products with minimum resource utilization. To ensure sustainability in manufacturing, three elements, i.e., processes, products and systems, must individually demonstrate the benefits at the social, economic and environmental levels [72]. Another definition considers sustainable manufacturing as "a value-added recovery process, which can recapture the value of the end-of-life product or discard product to its original distinctive value » [73]. In addition, Sustainable manufacturing plays a vital role in the circular economy to extend the life cycle of end-of-life and end-of-use items (18). Sustainable manufacturing is considered a subset of the circular economy [74].

Furthermore, the circular economy concept focuses on removing wastes through improved exploitation of resources [74]. There are various possibilities for defining CE [75]. We adopt the most cited definition proposed by the Ellen MacArthur Foundation [76]. This British charity association helps to propagate the principles of the circular economy and defines it as a "system restorative and regenerative by design, which aims to maintain products, components and materials at their highest utility and value". This foundation distinguishes between two flows, biological and technical.

2.4. Related works on Sustainability and Industry 4.0

Many studies have identified challenges, opportunities and the impact of Industry 4.0 technology adoption on sustainable manufacturing and circular economy (77; 78; 68; 71; 79; 80). Authors in (81) present the challenges of sustainable development and the key industry 4.0 elements which support these challenges. They discuss performance parameters in three dimensions—economic, social and ecological. [82] identify the barriers to sustainable operations in the era of Industry 4.0 and circular economy. [74] present a comparative analysis exploring opportunities for Industry 4.0 technologies and their potential impacts on sustainable manufacturing. [79] analyze the challenges in implementing Industry 4.0 technologies in SMEs for ethical and sustainable operations. Authors rank and categorize these challenges by the DEMATEL approach. A study in [83] investigates impacts using the Triple Bottom Line perspective for sustainable development. In this context, a model for evaluating the influence of Industry 4.0 technologies on sustainable metrics is proposed. This model analyses the impact of Industry 4.0 technologies on several key performance indicators related to sustainable development. [106] discuss how Industry 4.0 technologies can underpin circular economy strategies. The paper presents technologies on which organizations can base sustainable operations management decisions.

Other studies have proposed different sustainable manufacturing conceptual frameworks and architectures by applying Industry 4.0 technologies. [85] propose a sustainable framework to assist manufacturing organizations in the identification of barriers and also rank the solutions to overcome those barriers. [86] propose a conceptual framework of big data analytics in Sustainable smart manufacturing. The framework can be used as a guideline to select the relevant lifecycle stages that impact sustainable production. The work done in [87] Propose a new architecture which combines different technologies in order to propose a scalable architecture based on: CPS (responsible for establishing the real-time communication control network), digital-twin (responsible for fine perceptual control and simulation of the physical process); Big data (responsible for preprocessing; processing and storage of remanufacturing data) and IoT-Cloud (responsible for providing a software environment for Big Data Analysis). Based on these smart technologies, all the information is integrated to implement the prediction and optimization management for the product's multi-life-cycle remanufacturing process. The authors of [88] present the development of a decision-making framework to enable the remanufacturing of the Rechargeable Energy Storage System. This framework's novelty lies in identifying the exact data type and data sets required to enable remanufacturing, hence "data-driven remanufacturing".

The study in [89] develops a new framework by combining big data analytics, additive manufacturing and sustainable smart manufacturing technologies. An application scenario was also presented to demonstrate the proposed framework. Authors in [90] use supervised machine learning techniques to understand the environmental, economic and social impacts on the sustainability of food consumption. An integrated sustainability assessment and modeling framework is applied to 29 food consumption categories. The proposed framework involves five steps: (1) economic input-output life cycle sustainability assessment, (2) non-dimensional normalization, (3) sustainability performance evaluation, (4) centroid-based clustering analysis, and (5) sustainability impact modeling.

2.5. Multi-Agent System and Sustainability

A multi-agent system (MAS) is an artificial intelligence method used in our research to design and implement an open architecture that can support the integration of new logistics entities, processes, and decision-making criteria and indicators. A multi-agent system is defined as a set of entities that coordinate their knowledge, goals, experiences and plans to act or solve problems. Multi-agent systems distribute tasks between different agents (autonomous or semi-autonomous entities) in order to achieve their objectives in an optimal state. An agent can be defined as a computer system located in an environment from which it takes its input. The agent can act independently in this environment to meet its objectives [91].

Different researchers have used multi-agent systems to solve supply chain management problems, such as collaborative production planning, the collaboration of multiple logistics parties [92], coordination between enterprises, information sharing, order fulfillment process, provider selection, sustainable manufacturing [93], remanufacturing, etc. Regarding sustainability, several authors have applied MAS in developing sustainable manufacturing or sustainable supply chain. Other studies are focused on a specific activity, such as recycling, remanufacturing or repairing in reverse logistics. Our literature review on multi-agent systems applied in sustainable manufacturing allowed us to identify some related works. For example, authors in [94] present a system to implement a reverse production process following a Service-Oriented Manufacturing paradigm utilizing a virtual market. A multi-agent system supports this architecture to implement a virtual market for buying and selling products to be recycled (i.e. old materials, wastes, used items, etc.). This proposed system aims to facilitate stakeholders' participation in green supply chain activities. These activities are implemented using web services published in the cloud and managed by an SOA framework. [107] propose a Multi-Agent-based Personalised Product Service System. This architecture consists of a sensor agent module, a rating agent, a similarity agent, a user package agent, a system agent, a selection agent and a recommendation agent.

The authors propose a clothing rental service for male customers based on a specified set of needs. Thus, the agents cooperate in developing a personalized Product Service System (PSS). [96] propose to use collective intelligence techniques from multi-agent systems to implement a decision support system in remanufacturing context. This system transforms highly variable post-used components into new products using reuse-oriented strategies. A multi-agent system is also used to support decision-making process in recycling-oriented product assessment already at the design stage [97]. A study (Ghadimi, 2019) presents a system based on the multi-agent system for addressing sustainable supplier evaluation and selection process to provide a communication channel, structured information exchange and visibility among suppliers and manufacturers.

3. Proposed Architecture

This section details our proposed architecture, shown in the figure. 2. In our work, each level incorporates one or several agents. Agents communicate and collaborate between themselves to carry out the tasks entrusted to them [99]. Agents can work autonomously, make decisions independently, and interact with each other to achieve global objectives. The architecture supports the management of the reverse flows. Reverse logistics (RL) is the process initiated by the product returned by customers to suppliers. It is considered a key factor of sustainable manufacturing (100). Once the good has been collected and sorted, its fate has to be decided. Different options can be made, such as repair (if the product is defective), remanufacturing (for reselling to secondary markets or even for the main markets), recycling (to remove raw material), and the elimination of some parts or the entire product.

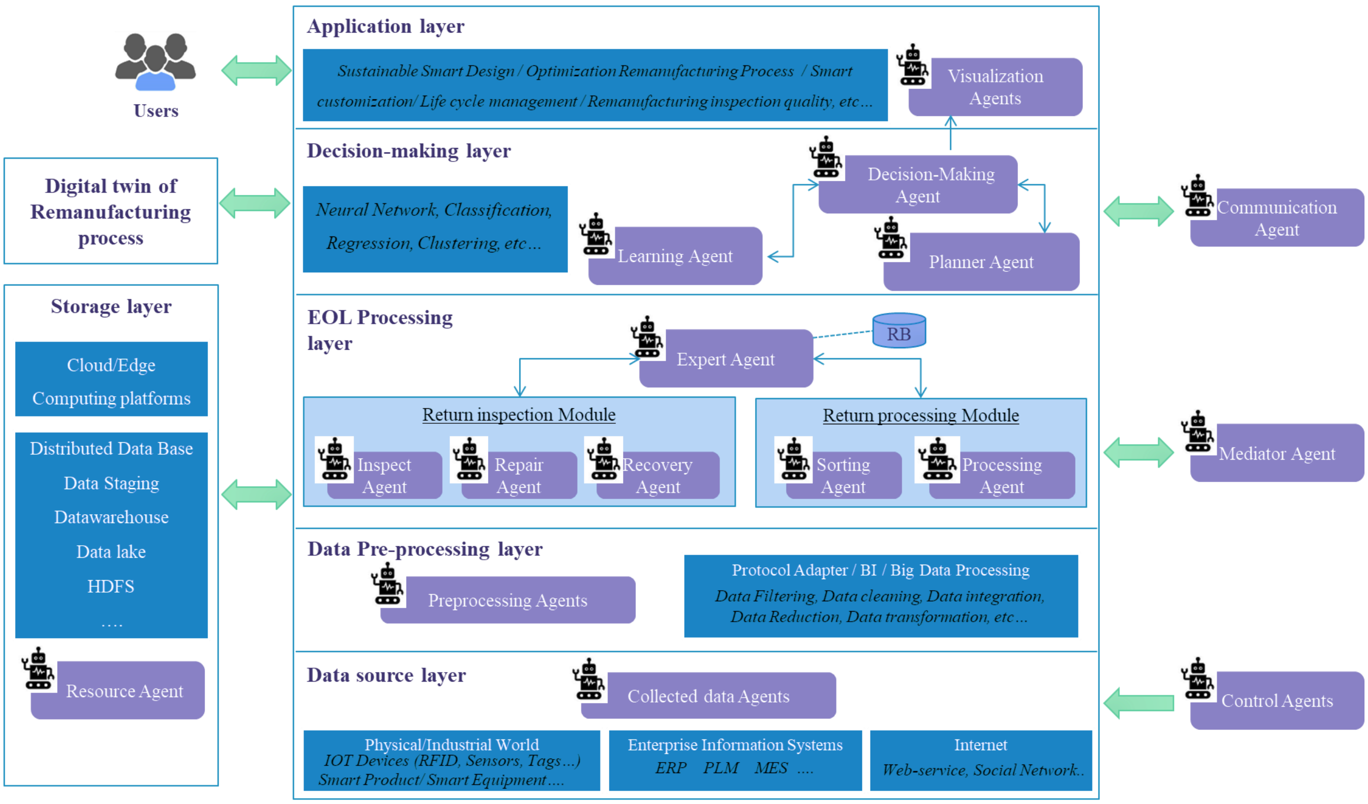

Fig. 2 Proposed architecture

3.1. Description of Layers

3.1.1. Data Source Layer

In order to procure the real-time data, some IoT devices are configured on the whole manufacturing cycle (smart design, smart production, smart delivery, smart recovery) and deployed to the products, in their locations or their parts (ex: the RFID device can be embedded into the products and record their lifecycle status). Other data can be acquired from the enterprise information systems (PLM, ERP, MES, etc.), including data about daily operations stored in transactional databases or else data of websites and web services. These data are used to monitor products during the different product lifecycle management processes and improve decision-making. Generally, we use two main data sources: internal (managed and controlled by the company) and external (not controlled by the company). These data are classified into three types [101]:

Structured Data

Structured data refers to data that has a fixed format organized into rows and columns, such as data stored in relational databases.

Unstructured Data

Unstructured data is data that does not have a specific format making it difficult to process; it can be textual (like emails, PowerPoint presentations, and Word documents) or non-textual (such as images, audio and video).

Semi-Structured

Semi-Structured is a form of structured data. It is not organized by the tabular structure but contains metadata tags to separate semantic elements contained therein. Email, SMS or XML documents are an example of semi-structured data.

Table 1. Data Example

Source	Data Type	Protocols/ Interfaces	Latency
Smart Devices	Degeneration status Temperature Shutdown problem	For data (MQTT, http, CoAP, etc.) For Network (Wifi, ZigBee, Z-Wave, etc.)	Real-time
Information system Database	Product type Sales volume number of returns	ODBC, OLEDB, JDBC, etc.	Batch

We need to use appropriate IOT technologies in this layer; a comparative study should be performed before implementation based on the following criteria: frequency bands, power consumption, range, cost, security, standards & throughput [104].

3.1.2. Data Preprocessing Layer

It is responsible for preparing real-time and non-real-time data captured from the data source layer (IOT sensors, RFID, database transaction...) to render them suitable for further processing and analysis. The data collected is heterogeneous; homogenization is required before transmitting it to the upper layers. This level includes the tasks of filtering, cleaning, reducing and transforming data. Data preparation consists of modifying and deleting incorrect, incomplete, irrelevant or repetitive data because such data is generally neither necessary nor useful for data processing and analysis. To complete the data preparation, we need to use in first the correct tool for ingestion. Our choice must depend on many parameters, such as data size, data format, data frequency or data velocity [102]. We classify two types of tools: Batch Data Ingestion, useful for offline analytics (e.g. Sqoop Apache) and Stream Data Ingestion (e.g. Flume Apache). The preparation layer loads the relevant data to the distributed storage layer (which supports the Hadoop ecosystem).

3.1.3. EOL Processing Layer

Each company's return process is defined and specific. However, generally, a product may be returned within the testing period for a refund or beyond the testing period for repair or replacement under warranty. If the product is no longer under warranty, others operations will be applied (including repairing with cost, remanufacturing, recycling, disposal, etc.). Our work (99) presents the generic returns handling supported by our multi-agent architecture. The process (represented by the Business Process Model and Notation approach) starts with controlling whether the product is accepted or rejected and whether it is a defective or end-of-life/end-of-use product. The agents of this level are initiated if the system requests returned products.

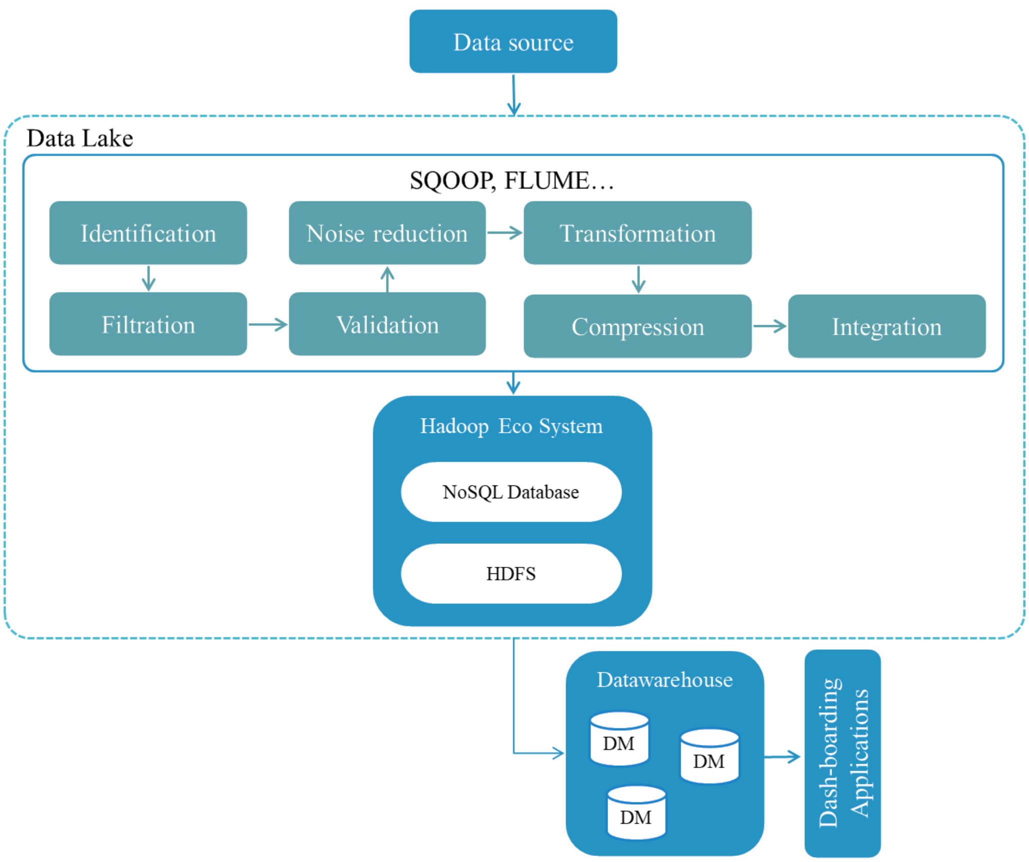

Fig. 3 Steps of data ingestion (adapted from Erraissi and al., 2018)

3.1.4. Decision-Making Layer

This layer offers different functionalities for decision-support. These functionalities could take the form of descriptive, predictive, and prescriptive analytics depending upon the need of the company and deployed tools. We propose a hybrid approach by implementing two principal modules: a reactive scheduling module (based on conventional methods) to optimize/adapt remanufacturing orders and sustainable manufacturing resources; and a learning module for data-driven modeling via machine learning algorithms. Indeed, predicting customers' returns, preferences, demands, the number of remanufactured parts, etc., are effective means for manufacturers to make their process more efficient and products better to customers' needs. This level uses the data generated directly by the data preprocessing layer and some results of the EOL processing layer to apply the learning models and predict the market requirements, helping manufacturers improve and develop the appropriate product for sustainable practices.

The combination of big data methods and machine learning models (e.g. clustering, classification, neural network, etc.) allows different knowledge to be revealed for decision-making. The deployment of machine learning models involves the use of two databases as well as different steps. The first step consists of determining the relevant data sources (learning data) and selecting the appropriate machine-learning algorithms that work best for the kind of prediction required by managers. In the next step, we use the chosen algorithm to improve the capacity of the predictive model (learning step). We move on to the evaluation step to test the predictive model with new data that has never been used by the learning (validation data). Then, we can improve our learning by adjusting the parameters. Otherwise, we move directly to the last step, which allows using the developed model to predict the expected results. The output of this level can be used for visualization via a human-machine interface or be sent to a physical environment so that control actions can be taken on the manufacturing supply chain.

3.1.5. Application Layer

Application layer provides the visualization of information and knowledge for end-users. Different application services can be proposed at this level (e.g. sustainable and smart product design, optimization of remanufacturing process, reduction in energy consumption, sustainable and smart maintenance, etc.) for efficient, sustainable smart manufacturing. At this level, we can use the outcoming of the decision-making layer or some data generated by Pre-processing layer (in this case, users can visualize KPIs on Business Intelligence dashboards or Decision Reports).

3.1.6. Storage Layer

We use in the first a relational database for the system's data storage. The collected data sets from the physical environment must be effectively integrated into the database/datawarehouse and be securely stored. So, manufacturing enterprises are focused principally on structured data storage but also manage the other categories of data. However, other data store technologies are used to manage large amounts and a variety of data, such as Distributed File Systems and NoSQL Databases.

3.1.7. Others Evolutif Layers

Our work consists of providing an opened and distributed architecture by integrating new functionalities and technologies. In this context, we can integrate a simulation module based on digital twins and the features of cloud computing. The cloud can provide the storage capability for the complete lifecycle of data processed by big data technologies. However, several challenges are involved in applying cloud storage to sustainable smart manufacturing, such as security, privacy and query optimization [86]. Regarding the digital twin, it provides rich information to support the production and recovery operation throughout the product lifecycle. Indeed, the product moves from the beginning-of-life (BOL) to middle-of-life (MOL) and end-of-life (EOL). Thus the knowledge and information maintained inside the digital twin become bigger and richer simultaneously and can be used for analysis and decision-making.

3.2. Description of Agents

The responsibilities of these agents, defined in Table 2, describe the generic behavior of each agent (the internal job that the agent has to do). Some agent functions may depend on the company's context.

Table 2. Responsibility table of proposed agents

Agents	Responsibilities
Communication Agent	Manages interactions between the whole system agents Uses the structure of FIPA ACL for managing the interaction between agents
Mediator Agent	Coordinates the various tasks of the system Decides which agent can be performed the tasks Initiates and sends requests to agents
Collected Data Agent	Acquires data from the data source layer Sends requests/information to the mediator
Preprocessing Agent	Receives requests from mediator agents for preparing and filtering data Handles missing and noisy data Transforms the data into appropriate forms for data analytics Sends the final data set obtained to the resource agent for storage

Inspect Agent	Receives requests from the mediator agent to inspect returned products Analyzes the characteristics of the returned products Checks if there are similar problems in its knowledge base using the Case-Bases Reasoning approach Requests sustainable processing rules from the expert agent Proposes solutions to manage the returns product Communicates the authorization number to the client (if the returned product is accepted) Informs the repairs agent or the recovery agent (depending on its decision) Informs the mediator agent of the proposed solution (After receipt of the results from the invoked agents) Requests the resource agent for data storage
Repair Agent	Receives requests from the inspection agent Takes care of the reparation's returned products to process Checks if the product is under warranty before proceeding to process Checks its knowledge base for managing the repair processing Informs the Inspect agent of the proposed solution Sends requests to the recovery agent if the product is not repairable
Recovery Agent	Receives request message from repair agent specifying that the returned product had to be recovered Select the appropriate rules to collect the product Decide which entities are responsible for the product recovery to optimize the customer collecting process at the collection site Informs the inspect agent of the proposed solution
Sorting Agent	Receives the confirmation of the returned product (end of life or end of use) from the mediator agent Separates the product into different components Checks the component's state and classifies them into reusable, recyclable or disposal Separates the components into hazardous and non-hazardous Checks its knowledge base for choosing the right option (based on past experience) Takes the best decision on processing options for EOL and EOU products (the main options supported by our process are recycling, resale, remanufacturing and disposal) Requests sustainable rules from the expert agent Sends the result sorting to the processing agent
Processing Agent	Supports the different steps of the chosen option (if the product needs to be recycled, remanufactured, disposed of, or reconfigured, etc.) Allocates the components to a particular processing unit according to their characteristics Informs the mediator agent of the final result (different data can be shared with the planner agent or directly with the decision-making agent via the mediator agent, ex: product state, component state, amount of components to be used, processing unit) Requests the resource agent for data storage
Expert Agent	Receives requests from the return inspection module's agents and return processing Module's agents Applies the rule-based reasoning technique for responding to requests (Its knowledge base contains different regulations, ex WEEE processing) Helps the other agents to make their decision Sends the sustainable processing rules (IF-ELSE) to requesting agents
Learning Agent	Exploits the data generated by preprocessing layer Receives requests from mediator agent Analyzes the features Chooses the appropriate algorithm to use Applies the learning model Evaluates the predictive model by testing it with new data Adjusts settings Sends the result to the decision agent
Planner Agent	Receives requests from mediator agent Applies the algorithms defined by the system designer (genetic algorithms, colony optimisation, etc.) according to the sustainable manufacturing problems Includes forecasting and remanufacturing planning capabilities (with the purpose of defining the optimal remanufacturing process plans in the dynamic production plants) Schedules the closed-loop supply chain operations Makes a decision as to when the components need to be transferred from the recovery warehouse Optimizes the resources

	Considers the consumer preferences in the selection of results Sends the result to the decision agent
Decision Agent	Takes different categories/levels of decisions Can receive the results generated by different agents: the processing agent, the learning agent or the planner agent. If it concerns learning, this agent applies the predictive model and infers knowledge Otherwise, here are some decision examples :Forecasting product returns, improving product design (simplifying the disassembly process), predicting customer demand, estimating different costs, etc. Sends the final decisions to visualization agents (to display information / KPI on the human-machine interface) Sends the final decisions to control the agent
Visualization Agent	Receives the final results from the decision agent Represent data to end users
Resource Agent	Receives requests for data Connects to database and datawarehouse and extracts the data Sends data to agents Records the data collected in real-time or batch mode
Control Agent	Receives the final results from the decision agent Performs actions directly in the physical environment via actuators

3.3. Agents Implementation: Future Perspectives

We will use the agent declaration, communication and interaction phase for system implementation on the JADE platform. The agent entity in the Jade platform is a class that inherits from "jade.core.Agent". This class contains the "setup" method, which is the initialization part of the agent. Each agent must be initialized and linked to one or more behaviors. It is considered a task that the agent must perform at a specific time and according to constraints. The definition of behaviors is carried out by "Behaviours", which allow agents to act in the JADE platform.

Behaviors are implemented as instances of a class inheriting from "jade.core.behaviours.Behaviour" and can contain at least two methods. The "action" method: defines the actions to perform when the behavior is invoked. The "done" method: returns a boolean indicating whether the behavior has finished executing or not.

The agents of our system use messages conforming to the FIPA-ACL specifications. The JADE platform uses ACL (Agent Communication Language) as an inter-agent communication language. ACL is based on communication acts that can be distinguished into three types:

- Informative
  query_if, subscribe, inform, inform_if confirm, disconfirm, not_understood
- Tasks distribution
  request, request_whenever, cancel, agree, refuse, failure
- Negotiation
  cfp, propose, accept_proposal reject_proposal

4. Conclusion

This paper presents our architecture platform for managing and predicting reverse flows in sustainability. Our main objective is to use industry 4.0 technologies, such exploitation of IOT and BIG DATA ecosystem.

The strengths of the presented architecture are (i) the use of the multi-agent system for more autonomy and intelligence and (ii) the ability to gather data from heterogeneous devices and tools to combine them on different artificial intelligence technologies. This architecture will serve as a roadmap for the future work of our research laboratory. In the following steps, we intend to implement the MAS application and use Machine Learning algorithms to develop a remanufacturing predicting case.

References

[1] Volkan Yavaş, and Yeşim Deniz Özkan-Özen, "Impacts of Industry 4.0 On Logistics Sector: A Theoretical Research Model Proposal," *International Caucasus-Central Asia Foreign Trade and Logistics Congress*, Didim/AYDIN, pp. 893-901, 2018.

[2] Ercan Oztemel, and Samet Gursev, "Literature Review of Industry 4.0 and Related Technologies," *Journal of Intelligent Manufacturing*, vol. 31, pp. 127–182, 2020. *Crossref*, https://doi.org/10.1007/s10845-018-1433-8

[3] B. Tjahjonoa et al., "What does Industry 4.0 Mean to Supply Chain?," *Manufacturing Engineering Society International Conference 2017, MESIC 2017,* Vigo (Pontevedra), Spain, vol. 13, pp. 1175-1182, 2017. *Crossref,* https://doi.org/10.1016/j.promfg.2017.09.191

[4] Yenumula B. Reddy, "Cloud-Based Cyber-Physical Systems: Design Challenges and Security Needs," *2014 10th International Conference on Mobile Ad-Hoc and Sensor Networks,* pp. 315-322, 2014. *Crossref,* https://doi.org/10.1109/MSN.2014.50

[5] John Fitzgerald et al., "Cyber-Physical Systems Design: Formal Foundations, Methods and Integrated Tool Chains," *2015 IEEE/ACM 3rd FME Workshop on Formal Methods in Software Engineering,* pp. 40-46, 2015. *Crossref,* https://doi.org/10.1109/FormaliSE.2015.14

[6] Ravinder Kumar, Rajesh Kr. Singh, and Yogesh Kr. Dwived, "Application of Industry 4.0 Technologies in Smes for Ethical and Sustainable Operations: Analysis of Challenges," *Journal of Cleaner Production*, vol. 275, p. 124063, 2020. *Crossref,* https://doi.org/10.1016/j.jclepro.2020.124063

[7] Ashraf Darwish, and Aboul Ella Hassanien, “Cyber-Physical Systems Design, Methodology, and Integration: The Current Status and Future Outlook,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 9, pp. 1541-1556, 2018. *Crossref*, https://doi.org/10.1007/s12652-017-0575-4

[8] Antoine Bagula, Olasupo Ajayi, and Hloniphani Maluleke, “Cyber-Physical Systems Dependability Using CPS-IOT Monitoring,” *Sensors*, vol. 21, no. 8, p. 2761, 2021. *Crossref*, https://doi.org/10.3390/s21082761

[9] Manu Suvarna et al., “Cyber-Physical Production Systems for Data-Driven, Decentralized, and Secure Manufacturing—A Perspective,” *Engineering*, vol. 7, no. 9, pp. 1212-1223, 2021. *Crossref*, https://doi.org/10.1016/j.eng.2021.04.021

[10] Li Da Xu, and Lian Duan, “Big Data for Cyber-Physical Systems in Industry 4.0: A Survey,” *Enterprise Information Systems*, vol. 13, no. 2, pp. 148-169, 2018. *Crossref*, https://doi.org/10.1080/17517575.2018.1442934

[11] Ting Zheng et al., “The Applications of Industry 4.0 Technologies in Manufacturing Context: A Systematic Literature Review,” *International Journal of Production Research*, vol. 59, no. 6, pp. 1922-1954, 2021. *Crossref*, https://doi.org/10.1080/00207543.2020.1824085

[12] Firouzeh Taghikhah, Alexey Voinov, and Nagesh Shukla, “Extending the Supply Chain to Address Sustainability,” *Journal of Cleaner Production*, vol. 229, pp. 652-666, 2019. *Crossref*, https://doi.org/10.1016/j.jclepro.2019.05.051

[13] Zahra Ahmadi-Gh, and Alejandro Bello-Pintado, “Why is Manufacturing Not More Sustainable? The Effects of Different Sustainability Practices on Sustainability Outcomes and Competitive Advantage,” *Journal of Cleaner Production*, vol. 337, p. 130392, 2022. *Crossref*, https://doi.org/10.1016/j.jclepro.2022.130392

[14] Rakesh R. Menon, and V. Ravi, “Analysis of Enablers of Sustainable Supply Chain Management in Electronics Industries: The Indian Context,” *Cleaner Engineering and Technology*, vol. 5, p. 100302, 2021. *Crossref*, https://doi.org/10.1016/j.clet.2021.100302

[15] T.Stock, and G.Seliger, “Opportunities of Sustainable Manufacturing in Industry 4.0,” *In Procedia CIRP*, vol. 40, pp. 536–541, 2016. *Crossref*, https://doi.org/10.1016/j.procir.2016.01.129

[16] Ricardo Chalmeta, and Nestor J. Santos-deLeón, “Sustainable Supply Chain in the Era of Industry 4.0 and Big Data: A Systematic Analysis of Literature and Research,” *Sustainability*, vol. 12, no. 10, p. 4108, 2020. *Crossref*, https://doi.org/10.3390/su12104108

[17] Theofilos D.Mastos et al., “Introducing an Application of an Industry 4.0 Solution for Circular Supply Chain Management,” *Journal of Cleaner Production*, vol. 300, p. 126886, 2021. *Crossref*, https://doi.org/10.1016/j.jclepro.2021.126886

[18] Deepak Singhala, Sushanta Tripathya, and Sarat Kumar Jena, “Remanufacturing for the Circular Economy: Study and Evaluation of Critical Factors,” *Resources, Conservation and Recycling*, vol. 156, p. 104681, 2020. *Crossref*, https://doi.org/10.1016/j.resconrec.2020.104681

[19] I.S.Jawahir, and Ryan Bradley, “Technological Elements of Circular Economy and the Principles of 6R-Based Closed-loop Material Flow in Sustainable Manufacturing,” *Procedia CIRP*, vol. 40, pp. 103–108, 2016. *Crossref*, https://doi.org/10.1016/j.procir.2016.01.067

[20] Inés Sittón Candanedo et al., “MASPI: A Multi Agent System for Prediction in Industry 4.0 Environment,” *International Joint Conference SOCO’18-CISIS’18-ICEUTE’18*, pp. 197-206, 2018. *Crossref*, https://doi.org/10.1007/978-3-319-94120-2_19

[21] Lucas Sakurada, and Paulo Leitão, “Multi-Agent Systems to Implement Industry 4.0 Components,” *2020 IEEE Conference on Industrial Cyberphysical Systems (ICPS)*, pp. 21-26, 2020. *Crossref*, https://doi.org/10.1109/ICPS48405.2020.9274745

[22] Shiyong Wang et al., “Towards Smart Factory for Industry 4.0: A Self-Organized Multi-Agent System with Big Data Based Feedback and Coordination,” *Computer Networks*, vol. 101, pp. 158-168, 2016. *Crossref*, https://doi.org/10.1016/j.comnet.2015.12.017

[23] Erik Hofmann, and Marco Rüsch, “Industry 4.0 and the Current Status as Well as Future Prospects on Logistics,” *Computers in Industry*, vol. 89, pp. 23-34, 2017. *Crossref*, https://doi.org/10.1016/j.compind.2017.04.002

[24] Lorenzo Ardito et al., “Towards Industry 4.0:Mapping Digital Technologies for Supply Chain Management-Marketing Integration,” *Business Process Management Journal*, vol. 25, no. 2, pp. 323-346, 2018. *Crossref*, https://doi.org/10.1108/BPMJ-04-2017-0088

[25] Beata Mrugalska, and Magdalena K.Wyrwicka, “Towards Lean Production in Industry 4.0,” *Procedia Engineering*, vol. 182, pp. 466-473, 2017. *Crossref*, https://doi.org/10.1016/j.proeng.2017.03.135

[26] Jian Qin, Ying Liu, and Roger Grosvenor, “A Categorical Framework of Manufacturing for Industry 4.0 and Beyond,” *Procedia CIRP*, vol. 52, pp. 173-178, 2016. *Crossref*, https://doi.org/10.1016/j.procir.2016.08.005

[27] Daniel Forgues et al., “From Industry 4.0 to Construction 4.0: Concrete Examples,” 2019.

[28] Fanny-Ève Bordeleau, Elaine Mosconi, and Luis Antonio Santa-Eulalia, “Business Intelligence in Industry 4.0: State of the Art and Research Opportunities,” 2018.

[29] Behzad Esmaeiliana et al., “Blockchain for the Future of Sustainable Supply Chain Management in Industry 4.0,” *Resources, Conservation & Recycling*, vol. 163, p. 105064, 2020. *Crossref*, https://doi.org/10.1016/j.resconrec.2020.105064

[30] Birgit Vogel-Heuser; and Dieter Hess, “Guest Editorial Industry 4.0–Prerequisites and Visions,” *IEEE Transactions on Automation Science and Engineering*, vol. 13, no. 2, pp. 411–413, 2016. *Crossref*, https://doi.org/10.1109/TASE.2016.2523639

[31] Valeria Belvedere, Andrea Chiarini, and Alberto Grando, “The Synergic Effect of Industry 4.0 Technologies on the Operations Performance, Evidence from Italy,” *25th International EurOMA Conference in Budapest*, Hungary, 2018.

[32] Jiani Zhang, “Cognitive Manufacturing & Industry 4.0,” *Internet of Things Blog*, 2017.

[33] Michael P. Papazoglou, “Metaprogramming Environment for Industry 4.0,” *International Conference on Enterprise System (ES)*, Limassol, pp. 18, 2018. *Crossref*, https://doi.org/10.1109/ES.2018.00008

[34] Sarah El Hamdi, Mustapha Oudani, and Abdellah Abouabdellah, “Morocco's Readiness to Industry 4.0,” *Proceedings of the 8th International Conference on Sciences of Electronics, Technologies of Information and Telecommunications (SETIT'18), SETIT 2018, Smart Innovation, Systems and Technologies, Springer,* vol. 146, pp. 463-472, 2018. *Crossref*, https://doi.org/10.1007/978-3-030-21005-2_44

[35] Xiaoxiao Xu et al., “Industrial Internet of Things for Smart Manufacturing Applications using Hierarchical Trustful Resource Assignment,” *Computer Communications,* vol. 160, pp. 423-430, 2020. *Crossref*, https://doi.org/10.1016/j.comcom.2020.06.004

[36] Wei Chen, “Intelligent Manufacturing Production Line Data Monitoring System for Industrial Internet of Things,” *Computer Communications,* vol. 151, pp. 31-41, 2020. *Crossref*, https://doi.org/10.1016/j.comcom.2019.12.035

[37] Asharul Islam Khana, and Ali Al-Badi, “Open Source Machine Learning Frameworks for Industrial Internet of Things,” *Procedia Computer Science*, vol. 170, pp. 571–577, 2020. *Crossref*, https://doi.org/10.1016/j.procs.2020.03.127

[38] Yu–Ju Lin, Ci-Bin Lan, and Chin-Yin Huanga, “A Realization of Cyber-Physical Manufacturing Control System Through Industrial Internet of Things,” *Procedia Manufacturing,* vol. 39, pp. 287-293, 2019. *Crossref*, https://doi.org/10.1016/j.promfg.2020.01.449

[39] Maribel Yasmina Santos et al., “A Big Data System Supporting Bosch Braga Industry 4.0 Strategy,” *International Journal of Information Management,* vol. 37, no.6, pp. 750-760, 2017. *Crossref*, https://doi.org/10.1016/j.ijinfomgt.2017.07.012

[40] Min Chen, Shiwen Mao, and Yunhao Liu, “Big Data: A Survey,” *Mobile Networks and Applications*, vol. 19, pp. 171–209, 2014. *Crossref*, https://doi.org/10.1007/s11036-013-0489-0

[41] Richard Crowder, “Cyber-Physical Systems and Security,” *Electric Drives and Electromechanical Systems*, pp. 271–289, 2020.

[42] Qinglin Qi et al., “Modeling of Cyber-Physical Systems and Digital Twin Based on Edge Computing, Fog Computing and Cloud Computing Towards Smart Manufacturing,” *ASME 2018 13th International Manufacturing Science and Engineering Conference,* 2018. *Crossref*, https://doi.org/10.1115/MSEC2018-6435

[43] Christian Matt, “Fog Computing: Complementing Cloud Computing to Facilitate Industry 4.0,” *Business &Information Systems Engineering*, vol. 60, pp. 351-355, 2018. *Crossref*, https://doi.org/10.1007/s12599-018-0540-6

[44] Jay Lee, “Industrial AI Applications with Sustainable Performance,” *Springer ebook,* 2020. *Crossref*, https://doi.org/10.1007/978-981-15-2144-7

[45] Ajil Ouahib et al., “A Comprehensive Review of Iot and Artificial Intelligence Technologies for the Development of Industry 4.0,” *International Conference in Operational Management and Supply Chain Management - CIMOCL'20*, FST de Settat, Morocco, 2020.

[46] Yuliang Yuna, Dexin Mab, and Meihong Yang, “Human-Computer Interaction-Based Decision Support System with Applications in Data Mining,” *Future Generation Computer Systems*, vol. 114, pp. 285-289, 2020. *Crossref*, https://doi.org/10.1016/j.future.2020.07.048

[47] Yuan Guo et al., “The Internet of Things-Based Decision Support System for Information Processing in Intelligent Manufacturing Using Data Mining Technology,” *Mechanical Systems and Signal Processing,* vol. 142, pp. 106630, 2020. *Crossref*, https://doi.org/10.1016/j.ymssp.2020.106630

[48] Harley Oliff, and Ying Liu, “Towards Industry 4.0 Utilizing Data-Mining Techniques: A Case Study on Quality Improvement,” *Procedia CIRP*, vol. 63, pp. 167-172, 2017. *Crossref*, https://doi.org/10.1016/j.procir.2017.03.311

[49] Miryam Barad, “Linking Cyber Security Improvement Actions in Healthcare Systems to Their Strategic Improvement Needs,” *Procedia Manufacturing*, vol. 39, pp. 279–286, 2019. *Crossref*, 10.1016/j.promfg.2020.01.335

[50] "Good Practice for Security of Internet of Things in the Context of Smart Manufacturing," *European Union Agency for Networked and Information Security (ENISA)*, 2018.

[51] Andrii Boikoa, Vira Shendrykb, and Olha Boiko, “Information Systems for Supply Chain Management: Uncertainties, Risks and Cyber Security,” *Procedia Computer Science*, vol. 149, pp. 65–70, 2019. *Crossref*, https://doi.org/10.1016/j.procs.2019.01.108

[52] QianYan et al., “A Review of 3D Printing Technology for Medical Applications,” *Engineering*, vol. 4, no. 5, pp. 729-742, 2018. *Crossref*, https://doi.org/10.1016/j.eng.2018.07.021

[53] Alessandro Ceruti et al.,“Maintenance in Aeronautics in an Industry 4.0 Context: The Role of Augmented Reality and Additive,” *Journal of Computational Design and Engineering,* vol. 6, no. 4, pp. 516-526, 2019. *Crossref*, https://doi.org/10.1016/j.jcde.2019.02.001

[54] Seung Ki Moon et al., “Application of 3D Printing Technology for Designing Lightweight Unmanned Aerial Vehicle Wing Structures,” *International Journal of Precision Engineering and Manufacturing-Green Technology*, vol. 1, no. 3, pp. 223–228, 2014. *Crossref*, https://doi.org/10.1007/s40684-014-0028-x

[55] Zhen Gao et al., “From Industry 4.0 to Robotics 4.0 - A Conceptual Framework for Collaborative and Intelligent Robotic Systems,” *Procedia Manufacturing*, vol. 46, pp. 591–599, 2020. *Crossref*, https://doi.org/10.1016/j.promfg.2020.03.085

[56] Chundong Wang et al., “How to Secure Autonomous Mobile Robots? An Approach with Fuzzing, Detection and Mitigation,” *Journal of Systems Architecture*, vol. 112, p. 101838, 2021. *Crossref*, https://doi.org/10.1016/j.sysarc.2020.101838

[57] Vinu Vijayakumaran Nair, Daniel Kuhn, and Vera Hummel, “Development of an Easy Teaching and Simulation Solution for an Autonomous Mobile Robot System,” *Procedia Manufacturing*, vol. 31, pp. 270–276, 2019. *Crossref*, https://doi.org/10.1016/j.promfg.2019.03.043

[58] ShirineEl Zaatari et al., “Cobot Programming for Collaborative Industrial Tasks: An overview,” *Robotics and Autonomous Systems*, vol. 116, pp. 162-180, 2019. *Crossref*, https://doi.org/10.1016/j.robot.2019.03.003

[59] Sebastian Haag, and Reiner Anderl, “Digital Twin- Proof of Concept,” *Manufacturing Letter*, vol. 15, pp. 64-66, 2018. *Crossref*, https://doi.org/10.1016/j.mfglet.2018.02.006

[60] Fei Tao et al., “Digital Twin-Driven Product Design, Manufacturing and Service with Big Data,” *The International Journal of Advanced Manufacturing Technology*, vol. 94, pp. 3563-3576, 2018. *Crossref*, https://doi.org/10.1007/s00170-017-0233-1

[61] Cordula Czwick, and Reiner Anderl, “Cyber-Physical Twins - Definition, Conception and Benefit,” *Procedia CIRP*, vol. 90, pp. 584-588, 2020. *Crossref*, https://doi.org/10.1016/j.procir.2020.01.070

[62] Information Report, 2018. [Online]. Available: http://www.assemblee-nationale.fr/dyn/15/rapports/micblocs/l15b1501_rapport-information

[63] Jay Lee, Moslem Azamfar, and Jaskaran Singh, “A Blockchain Enabled Cyber-Physical System Architecture for Industry 4.0 Manufacturing Systems,” *Manufacturing Letters*, vol. 20, pp. 34-39, 2019. *Crossref*, https://doi.org/10.1016/j.mfglet.2019.05.003

[64] Gun-Yeal Lee et al., “Metasurface Eyepiece for Augmented Reality,” *Nature Communications*, vol. 9, p. 4562, 2018. *Crossref*, https://doi.org/10.1038/s41467-018-07011-5

[65] Omer Kavrar, "Energy Accounting and Sustainability: Analysis of Energy Performance in a Manufacturing Company," *SSRG International Journal of Economics and Management Studies*, vol. 7, no. 6, pp. 76-84, 2020. *Crossref*, https://doi.org/10.14445/23939125/IJEMS-V7I6P112

[66] J Jong-Young Hong et al., “See-Through Optical Combiner for Augmented Reality Head-Mounteddisplay: Index-Matched Anisotropic Crystal Lens," *Scientific Reports*, vol. 7, p. 2753, 2017. *Crossref*, https://doi.org/10.1038/s41598-017-03117-w

[67] Aldo Faisal, “Computer Science: Visionary of Virtual Reality,” *Nature*, vol. 551, pp. 298–299, 2017. *Crossref*, https://doi.org/10.1038/551298a

[68] Surajit Bag, and Jan Harm Christiaan Pretorius, “Relationships between Industry 4.0, Sustainable Manufacturing and Circular Economy: Proposal of a Research Framework,” *International Journal of Organizational Analysis*, vol. 30, no. 4, pp. 864-898, 2022. *Crossref*, https://doi.org/10.1108/ijoa-04-2020-2120

[69] Bjoern Jaeger, and Arvind Upadhyay, “Understanding Barriers to Circular Economy: Cases from the Manufacturing Industry,” *Journal of Enterprise Information Management*, vol. 33, no. 4, pp. 729-745, 2020. *Crossref*, https://doi.org/10.1108/jeim-02-2019-0047

[70] Hao Zhang, and Karl R. Haapala, “Integrating Sustainable Manufacturing Assessment Into Decision Making for a Production Work Cell,” Journal of Cleaner Production, vol. 105, pp. 52-63, 2015. *Crossref*, https://doi.org/10.1016/j.jclepro.2014.01.038

[71] Antonio Sartal et al., “The Sustainable Manufacturing Concept, Evolution and Opportunities within Industry 4.0: A Literature Review,” *Advances in Mechanical Engineering*, vol. 12, no. 5, 2014. *Crossref*, https://doi.org/10.1177/1687814020925232

[72] Anbesh Jamwal et al., “Industry 4.0 Technologies for Manufacturing Sustainability: A Systematic Review and Future Research Directions,” *Applied Sciences*, vol. 11, no. 12, p. 5725, 2021. *Crossref*, https://doi.org/10.3390/app11125725

[73] Heng Jong Ngu, Man Djun Lee, and Mohd Shahril Bin Osman, “Review on Current Challenges and Future Opportunities in Malaysia Sustainable Manufacturing: Remanufacturing Industries,” *Journal of Cleaner Production*, vol. 273, p. 123071, 2020. *Crossref*, https://doi.org/10.1016/j.jclepro.2020.123071

[74] Enyoghasi C., and Badurdeen, F., “Industry 4.0 for Sustainable Manufacturing, Opportunities at the Product, Process, and System Levels,” *Resources, Conservation and Recycling*, vol. 166, no. 1, p. 105362, 2021. *Crossref*, https://doi.org/10.1016/j.resconrec.2020.105362

[75] Okechukwu Okorie et al., “Digitisation and the Circular Economy: A Review of Current Research and Future Trends,” *Energies*, vol. 11, no. 11, p. 3009, 2018. *Crossref*, https://doi.org/10.3390/en11113009

[76] Ellen Mac Arthur Foundation, “Toward the Circular Economy: Economic and Business Rationale for an Accelerated Transition,” pp. 1–97, 2013.

[77] Sunil Luthra, and Sachin Kumar Mangla, “Evaluating challenges to Industry 4.0 Initiatives for Supply Chain Sustainability in Emerging Economies,” *Process Safety and Environmental Protection*, vol. 117, pp. 168–179, 2018. *Crossref*, https://doi.org/10.1016/j.psep.2018.04.018

[78] Mohamed Abubakr et al., “Sustainable and Smart Manufacturing: An Integrated Approach,” *Sustainability*, vol. 12, no. 6, p. 2280, 2020. *Crossref*, https://doi.org/10.3390/su12062280

[79] Ravinder Kumar, Rajesh Kr. Singh, and Yogesh Kr. Dwivedi, “Application of Industry 4.0 Technologies in Indian SMEs for Sustainable Growth: Analysis of Challenges,” *Journal of Cleaner Production*, vol. 275, p. 124063, 2020. *Crossref*, https://doi.org/10.1016/j.jclepro.2020.124063

[80] Peter Onu, and Charles Mbohwa, “Industry 4.0 Opportunities in Manufacturing SMEs: Sustainability Outlook,” *Materials Today: Proceedings*, vol. 44, pp.1925-1930, 2021. *Crossref*, https://doi.org/10.1016/j.matpr.2020.12.095

[81] Sangwan S.R, and Bhatia M.P.S, “Sustainable Development in Industry 4.0, in a Roadmap to Industry 4.0: Smart Production, Sharp Business and Sustainable Development,” *Advances in Science, Technology & Innovation; Springer: Cham*, Switzerland, 2020.

[82] Pravin Kumar, Rajesh Kr Singh, and Vikas Kumar, “Managing Supply Chains for Sustainable Operations in the Era of Industry 4.0 and Circular Economy: Analysis of Barriers,” *Resources, Conservation and Recycling*, vol. 164, p. 105215, 2021. *Crossref*, https://doi.org/10.1016/j.resconrec.2020.105215

[83] Elpidio Oscar Benitez Nara et al., “Expected Impact of Industry 4.0 Technologies on Sustainable Development: A Study in the Context of Brazil's Plastic Industry,” *Sustainable Production and Consumption*, vol. 25, pp. 102-122, 2021. *Crossref*, https://doi.org/10.1016/j.spc.2020.07.018

[84] V Ramana Reddy, and E SakshalSreeman, "Sustainable aspects of Green Supply Chain Management in Manufacturing Environment," *SSRG International Journal of Industrial Engineering,* vol. 3, no. 3, pp. 17-22, 2016. *Crossref,* https://doi.org/10.14445/23499362/IJIE-V3I5P104

[85] Javed Malek, and Tushar N.Desai, “A Framework for Prioritizing the Solutions to Overcome Sustainable Manufacturing Barriers,” *Cleaner Logistics and Supply Chain,* vol. 1, p. 100004, 2021. *Crossref,* https://doi.org/10.1016/j.clscn.2021.100004

[86] Shan Ren et al., “A Comprehensive Review of Big Data Analytics throughout Product Lifecycle to Support Sustainable Smart Manufacturing: A Framework, Challenges and Future Research Directions,” *Journal of Cleaner Production*, vol. 210, pp. 1343-1365, 2019. *Crossref,* https://doi.org/10.1016/j.jclepro.2018.11.025

[87] Yankai Wang et al., “Big data driven Hierarchical Digital Twin Predictive Remanufacturing paradigm: Architecture, Control Mechanism, Application Scenario and Benefits,” *Journal of Cleaner Production*, vol. 248, p. 119299, 2020. *Crossref,* https://doi.org/10.1016/j.jclepro.2019.119299

[88] O.Okorie et al., “A Decision-Making Framework for the Implementation of Remanufacturing in Rechargeable Energy Storage System in Hybrid and Electric Vehicles,” *Procedia Manufacturing,* vol. 25, pp. 142-153, 2018. *Crossref,* https://doi.org/10.1016/j.promfg.2018.06.068

[89] Arfan Majeed et al., “A Big Data-Driven Framework for Sustainable and Smart Additive Manufacturing,” *Robotics and Computer-Integrated Manufacturing*, vol. 67, p. 102026, 2021. *Crossref,* https://doi.org/10.1016/j.rcim.2020.102026

[90] Galal M. Abdella et al., “Sustainability Assessment and Modeling Based on Supervised Machine Learning Techniques: The Case for Food Consumption,” *Journal of Cleaner Production,* vol. 251, p. 119661, 2020. *Crossref,* https://doi.org/10.1016/j.jclepro.2019.119661

[91] Tope Roseline Olorunfemi, and Nnamdi I. Nwulu, “Multi-Agent Based Optimal Operation of Hybrid Energy Sources Coupled with Demand Response Programs,” *Sustainability*, vol. 13, no. 14, p. 7756, 2021. *Crossref,* https://doi.org/10.3390/su13147756

[92] Dan Yang et al., “Understanding the Effect of Multi-Agent Collaboration on the Performance of Logistics Park Projects: Evidence from China,” *Sustainability,* vol. 14, no. 7, p. 4179, 2022. *Crossref,* https://doi.org/10.3390/su14074179

[93] Adriana Giret et al., “A Holonic Multi-Agent Methodology to Design Sustainable Intelligent Manufacturing Control Systems,” *Journal of Cleaner Production*, vol. 167, pp. 1370-1386, 2017. *Crossref,* https://doi.org/10.1016/j.jclepro.2017.03.079

[94] Adriana Giret, and Miguel A. Salido, “A Multi-Agent Approach to Implement a Reverse Production Virtual Market in Green Supply Chains,” *Advances in Production Management Systems,* vol. 514, pp. 399-407, 2017. *Crossref,* https://doi.org/10.1007/978-3-319-66926-7_46

[95] Raj KishorPradhan, and Bibhudatta Sahoo, "A Case Study of Sustainable Development of Global Economics," *SSRG International Journal of Economics and Management Studies*, vol. 9, no. 3, pp. 48-52, 2022. *Crossref,* https://doi.org/10.14445/23939125/IJEMS-V9I3P106

[96] Mickaël Bettinelli et al., “A Decision Support Framework for Remanufacturing of Highly Variable Products Using a Collective Intelligence Approach,” *Procedia CIRP*, vol. 90, pp. 594-599, 2020. *Crossref,* https://doi.org/10.1016/j.procir.2020.06.003

[97] Ewa Dostatni et al., “Multi-Agent System to Support Decision-Making Process in Design for Recycling,” *Soft Computing,* vol. 20, no. 11, pp. 4347–4361. *Crossref,* https://doi.org/10.1007/s00500-016-2302-z

[98] Pezhman Ghadimi et al., “Intelligent Sustainable Supplier Selection Using Multi-Agent Technology: Theory and Application for Industry 4.0 Supply Chains,” *Computers & Industrial Engineering,* vol. 127, pp. 588-600, 2019. *Crossref,* https://doi.org/10.1016/j.cie.2018.10.050

[99] Nawal Bensassi et al., “Multi-Agent Architecture for Managing Return Flows,” *2018 International Colloquium on Logistics and Supply Chain Management (LOGISTIQUA),* pp. 1-6, 2018. *Crossref,* https://doi.org/10.1109/LOGISTIQUA.2018.8428281

[100] Jalil Baddaoui, Abdelhakim Nassimi, and Zouadi Tarik, “Sustainable Supply Chain and Reverse Logistics Management: An Empirical Study in the Moroccan Automotive Sector,” *Conference: International Conference on Industrial Engineering and Operations Management,* Morocco, pp. 1071-1079, 2017.

[101] Allae Erraissi, Abdessamad Belangour, and Abderrahim Tragha “Meta-Modeling of Data Sources and Ingestion Big Data Layers,” *SSRN Electronic Journal,* 2018. *Crossref,* https://doi.org/10.2139/ssrn.3185342

[102] Jaber Alwidian et al., “Big Data Ingestion and Preparation Tools,” *Modern Applied Science,* vol. 14, no. 9, pp. 12-27, 2020. *Crossref,* https://doi.org/10.5539/mas.v14n9p12

[103] Chetan S Patange, Aruntigadi, and Sadanand B Kulkarni, "Survey on Industry 4.0," *International Journal of Engineering Trends and Technology,* vol. 67, no. 5, pp. 153-159, 2019. *Crossref,* https://doi.org/10.14445/22315381/IJETT-V67I5P226

[104] Neeraj Kaushik, Dr. Teena Bagga, and Dr. Rashmi K Aggarwal, “Comparative Study on IoT Technologies - Short & Long Range,” *International Journal of Engineering Trends and Technology,* vol. 68, no. 12, pp. 37-42, 2020. *Crossref,* https://doi.org/10.14445/22315381/IJETT-V68I12P207

[105] Lorenzo Damiani et al., “Augmented and Virtual Reality Applications in Industrial Systems: A Qualitative Review Towards the Industry 4.0 Era,” *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 624–630, 2018. *Crossref,* https://doi.org/10.1016/j.ifacol.2018.08.388

[106] Ana Beatriz Lopes de Sousa Jabbour et al., "Industry 4.0 and the Circular Economy: A Proposed Research Agenda and Original Roadmap for Sustainable Operations," *Annals of Operations Research, Springer*, vol. 270, no. 1, pp. 273-286, 2018. *Crossref,* https://doi.org/10.1007/s10479-018-2772-8

[107] Ming-Chuan Chiu, and Chi-Hsuan Tsai, “Design a Personalised Product Service System Utilising a Multi-Agent System,” *Advanced Engineering Informatics,* vol. 43, p. 101036, 2020. *Crossref,* https://doi.org/10.1016/j.aei.2020.101036