When Industry 4.0 meets End-of-Life Aircraft treatment: A brief review and criteria for identifying the core technologies

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Abstract. Only a few studies discuss the applications of industry 4.0 in the context of end-of-life aircraft treatment. This paper aims to discuss the implications of these technologies in end-of-life aircraft processes. The selected technologies including blockchain, the internet of things, digital twins, big data, artificial intelligence, augmented/virtual reality, collaborative robots are discussed. In addition, the criteria to evaluate the different technologies and a conceptual model for selecting the core technologies will be presented.

Keywords: Industry 4.0, End-of-life aircraft, Analytical Network Process (ANP)

1 Introduction

The aerospace industry is more and more challenged by the growing disposal of end-of-life (EoL) aircraft [54]. Indeed, more than 15,000 aircraft are projected to reach the end of their life in two decades [2]. Despite the growth of EoL aircraft, the status quo remains the disposal in deserts [10, 41]. There are several alternatives to EoL aircraft treatment and thus several initiatives are taking place. AFRA (Aircraft Fleet Recycling Association) focuses on decommissioning aircraft in the most sustainable way [1]. The European Commission introduced the PAMELA project which stands for the Process for Advanced Management of EoL aircraft and aims to dispose of aircraft in the most sustainable and safe way possible [12]. The performance of EoL management can be increased with the help of industry 4.0 and its tool. Industry 4.0 in the EoL context is a new field of study that started in the mid-2010s [8]. Only a limited amount of literature addresses EoL products and industry 4.0 implications [38]. This paper aims to address the applications of industry 4.0 technologies in the EoL aircraft context and introduce a conceptual framework for evaluating the relationship and performance of the core technologies. This study's contributions are as follows:

- Identifying the implications of Industry 4.0 in EoL aircraft context considering the operational context
- Developing a multi-criteria decision framework for identifying the key criteria for evaluating the industry 4.0 technologies

The rest of the paper is organized as follows; the literature on EoL aircraft treatment processes and subprocess is discussed. After that, a brief literature review is provided on industry 4.0 technologies that are used or can be used in the EoL context. Then, a synthesis is provided for classifying the relation between aircraft processes and industry 4.0 technologies and a preliminary conceptual model to choose the core technologies is presented. Finally, the conclusion is presented with some remarks and the future research direction.

2 End-of-Life aircraft

2.1 Aircraft decommissioning processes.

There is no specific standard for an efficient decommissioning process of EoL aircraft [27]. Authors discuss four steps for the EoL aircraft treatments: decontamination, disassembly, dismantling and material recovery or landfill. IATA presented the "Best Industry Practices for Aircraft Decommissioning" (BIPAD) [17]. First, the aircraft go through decontamination of hazardous material (HAZMAT) and other non-desirable substances. After, in the disassembling step, valuable components such as the engine, avionics, and landing gears will be extracted (figure 1). To reuse those valuable components, it is necessary to recertify them and keep their airworthiness status through reverse logistics (RL) phases. After the disassembling, the dismantling step is processed for recycling needs. The final phase is to sort the components and material left into two categories, the recyclable, and the non-recyclable which will go to the scrap and landfilled. The aircraft is a complex product that can attain 2.3 million components as the Boeing 787 [52]. As a result, the challenging tasks of disassembly and dismantling require smart sorting and advanced technologies to prioritize the disassembly and dismantling process.

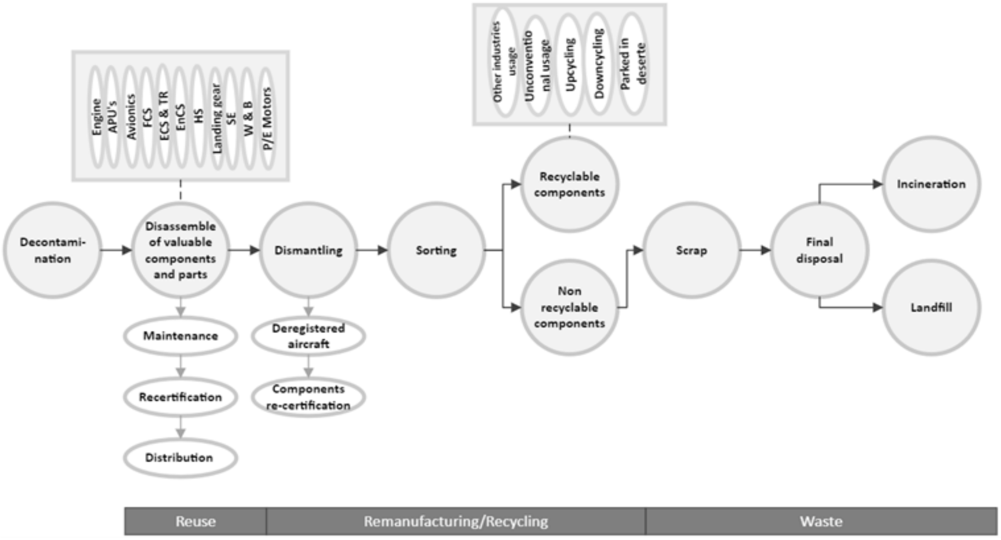

Figure 1- EoL aircraft decommissioning processes (Based on information in [17])

***APU**: Auxiliary Power Unit; **FCS**: Flight Control System **ECS & TR**: Engine Control System & Thrust Reverser; **EnCS**: Envionmental Control System; **HS**: Hydraulic Systems; Landing gear; **SE**: Safety Equipment; **W&B**: Wheels and Brakes; **P/E Motors**: Pump and Electric Motors*

2.2 Proposed approaches for addressing EoL aircraft problem

Several models and guidelines have been proposed for the management of EoL aircraft. Some of the literature attempts to tackle the problem at its source and focuses on the very first stage of product development: the design phase. In this phase, there is a lack of thinking about the end of the product's life [43]. Sabaghi and al. used multicriteria decision-making (MCDM) to assess the EoL aircraft disassembly process [43]. They suggest a difficulty disassembly indicator to measure the level of complexity of disassembly tasks. Five parameters have been chosen through literature and experts' opinions and they combined the DOE-TOPSIS method to run this MCDM problem. The first parameter is the accessibility of the parts that need to be disassembled. The second is the 'mating face' complexity of two components merged or more. The third is the 'tools' used to disassemble, and the fourth parameter is the 'connection type' that influenced the complexity of the disassembly. The final parameter is the 'quantity and variety of connections. Ribeiro et al. [41], introduced a framework in the preliminary design for the treatment of EoL aircraft and addresses economic and environmental factors. The framework aims to integrate the 3R approach (reuse, recycle and remanufacture) at the design phase. They focused on the EoL phase during the conceptual design phase, as this is an important stage for the designer, who needs feedback from EoL phase. The framework uses requirements and aircraft information such as the sizing of components and detailed design to develop the EoL part. Then, an estimation of performance parameters is analyzed, and a Life Cycle Assessment (LCA) is completed with simulation to find the optimum final aircraft design. Eco-design thinking can be used to optimize the EoL process by reducing the environmental impact in a cost-effective manner [27]. Eco-design used with LCA can design a better product by considering environmental impacts during the life cycle (LC) with less cost and low social impacts [45].

Other studies have proposed application of the LCA approach to evaluate the impact of decommissioning, dismantling, or disassembling an EoL aircraft to optimize its sequences with the triple bottom line objectives (economic, environmental, and social) [15, 40-41,47, 56]. Howes et al. [15] also used LCA assessment to determine the consequences of decommissioning on the environment. Domingues and al. [11] used the LCA in decision-making by combining it with MCDM methods to analyze the environmental impacts of different vehicles. LCA evaluates the environmental impacts of vehicles' alternatives and the MCDM methods classified the alternatives based on the different indicators: 'abiotic depletion, acidification, eutrophication, fuel consumption, global warming, photochemical oxidation, NOx, CO, particulate matter, and ozone layer depletion' [11]. Zahedi et al. [53] proposed a model to evaluate and optimize disassembly for EoL aircraft processing and to minimize the environmental impact. They developed the 'disassembly difficulty indicator' that measures the complexity of a disassembly sequence in a semi-destructive EoL aircraft context. This model also guides designers in making future-generation planes with more EoL-oriented incentives. Application of Industry 4.0 technology in the LC of complex products is a fresh research theme. More empirical studies are required to assess the challenges and discuss the application perspectives. In this research, EoL aircraft treatment will be considered for examining and evaluating the impact of advanced technologies for improving the complex product recovery network.

3 End-of-life 4.0

3.1 Industry 4.0 and EoL aircraft treatment

The 4th industrial revolution, known as Industry 4.0, gave access to several disruptive technologies that can improve the management of EoL products [19]. Its technologies help preserve the value of a product. Several of those technologies can be used to preserve the value of a product through its life cycle and supply chain, such as blockchain, Internet of Things (IoT) and Big Data. [22]. The EoL treatment in the context of industry 4.0 can be referred to as ‘EoL 4.0’. As opposed to manufacturing inputs, recycled inputs can be damaged by use, bent, twisted, deformed, or even fatigued [38]. Advanced technologies help predict the remaining useful life (RUL) and fatigue [51], track and exchange data in real-time [38] that can reinforce partnerships with the different stakeholders involved in the reverse supply chain and increase the quality of resources. Furthermore, the EoL 4.0 context is interesting in western countries because it diminishes labor shortage [38, 50]. The following subsections discuss the application technologies under the umbrella of Industry 4.0 in EoL product treatment.

Application of Blockchain and Internet of Things.

Blockchain could address a certain challenge regarding EoL aircraft. Keivanpour [20] proposed to use blockchain for the EoL aircraft recovery part market for its traceability features and smart contract possibilities. Blockchain can also provide better data security, better visibility in the supply chain through traceability and improved information sharing. This technology can also be used for its safety guarantees and auditable easy outcomes [48]. Aleshi and al. [3] used blockchain technology to propose a Secure Aircraft Maintenance Record (SAMR) to address the need to provide greater integrity and transparency of aircraft maintenance records. The radio-frequency identification (RFID) system combined with blockchain technology contributes to the complex credentials and documents that need to be collected for the certification of an aircraft. It will improve the efficiency of the process and the reliability of these documents all along the supply chain [44].

The IoT can also be applied in the supply chain to enable traceability features. Maintenance traceability is critical in the aerospace sector as more than 20,000 aircraft components will be replaced throughout their LC [48]. The authors highlighted the lack of standardized records and traceability for the aircraft use of materials, maintenance. In response to this, [44] proposed to combine the RFID tag system with IoT technology in Airbus’ supply chain. This could be achieved through blockchain processes that simplify information access and increase data security. However, the combination of IoT and RFID has some limitations, such as energy consumption, data synchronization, intercommunication difficulties and safety [19]. Wang and Li designed a model that uses blockchain and IoT to create a framework for monitoring the supply chain to ensure that airworthiness traceability is met for the entire LC of an aircraft [48].

Application of Digital Twin

Digital twin (DT) technology provides a digital copy of a physical object with real-time data transfer information. It can help to simulate and optimize dismantling or disassembling processes with better efficiency through data optimization [19]. It was initially introduced by NASA and shifted from spatial simulation to aircraft [31,49]. DT application in the EoL stage is the least studied topic in the life cycle of a product with only 4.9% [25]. This technology can fulfil different roles: it can diagnose a problem or predict a scenario in a disassembly process of a component via simulation [25]. These different roles can be addressed by providing real-time data in a decentralized manner. Indeed, DT integrates the proper information at the correct time in the product's life cycle. This leads to the enhancement of material flow and helps to adopt the circular economy by allowing transparency and improved collaboration between the different stakeholders. With the availability of information in real time, the different actors can anticipate and foresee possible problems and act accordingly in the value chain. Hence, collaboration is simplified in this way [36]. Moreover, digital technologies help the transition to the circular economy model by making data accessible through transparency. This enables reverse material flows [34] and can be called a 'digital reverse logistic twin' [46]. DT enables reverse flow by using artificial intelligence to predict the data behavior of the physical and digital world combined with the use of a mathematical model to simulate the critical parameters for a quantitative decision model [18, 46]. The digital mirror model enables simulation with high reliability. Wang and Wang [49] proposed using DT in recovery, recycling, and remanufacturing processes for waste from electric and electronic equipment (WEEE). They presented the WEEE cyber-physical system based on DT technology and through product life cycle. This system is based on a cloud system and includes:

- Design phase: an LCA is made to assess environmental impact and simulation for design for recycling, disassembly, remanufacturing, and archiving when needed.
- Manufacturing and remanufacturing phases: CAx model
- Consumer: attached tag of tracking/identification technology (e.g., RFID, QR code) so they can update information for repair, replacement, or upgrade through an application. These technologies are static and are linked to a DT that becomes unique at this phase. This DT supports different recycling, and remanufacturing EoL activities. It is personalized and procures a competitive advantage by its adaptability to scenarios, simulations, and clients' requirements.
- EoL collecting and recycling: collecting is generated with a computer-aided logistic system (CALS) and is driven based on the most recent system status.
- Remanufacturing phase: DT is based on the product history data, and a plan is made for optimized recycling processes.

DT technology can be integrated with other industry 4.0 technologies such as RFID, artificial intelligence, or different cyber-physical systems. International standards are designed to support interoperability in these diverse systems [49].

Application of Big data and Artificial Intelligence

Data plays an essential role in the aviation industry. To optimize EoL processes, a significant volume of data is required throughout the life cycle of an aircraft. Specifically, data mining can provide a better understanding and decision-making in the different stages during the treatment of an EoL aircraft [19]. Big data analysis (BDA) enables 'smart decision-making' as the data permit to predict maintenance and other product behavior [57]. A big set of data permits the use of algorithms. Mascle and Balasoiu [28] use the wave propagation algorithm to propose an optimal disassembly analysis and sequence execution. Ding and al. have used data technology for the remanufacturing of EoL goods. Indeed, they used this technology to predict and optimize the cost for the remanufacturing step and to propose a cost model [9]. [55] created an architecture with BDA for cleaner maintenance of complex products.

Artificial intelligence (AI) and machine learning (ML) are broadly utilized for the remaining useful life (RUL) [51] and in the RL for disassembly, remanufacturing, and recycling [22]. Amin and Kumar [4] used AI to propose a model for forecasting the residual operating life of a turbofan aircraft engine. They used NASA's commercial-Modular Aero-Propulsion System data sets. First, they used sensors to measure different raw data such as temperature, pressure, speeds, fuel flow and coolant bleed. After, the authors used the min-max normalization method within the [-1,1] range and used a two-dimension matrix with sensor data and time sequences. These data were used with the deep learning method of Convolutional Neural Network that flattered outputs for the next step. In the next step, the long-short-term memory layer or the recurrent neural network layers were used and compared for the remaining useful life prediction with a single neuron attached at the end to provide the result. After this step, a performance evaluation is made with a root mean squared error and simulations are performed [4]. AI allows for the introduction of more intelligent technologies such as augmented and virtual reality (AR / VR), as discussed further below, through its human-like intelligence and discernment. ML can be used in the disassembly process. Grochowski and Tang [13] aimed to apply ML to be cost-efficient through the disassembly processes. There are two principal challenges for the disassembly sequence: first, the modulization of the disassembly process can be complex because it is necessary to know what activity needed to be performed at any moment during the disassembly. For this matter, the authors proposed to use the disassembly Petri net (DPN) that represents a non-deterministic decision-making model during disassembly. However, DPN cannot be used alone because it doesn't acknowledge which actions are the most appropriate to take. To respond to this challenge, the hybrid Bayesian network (HBN) is combined with DPN. It determines the uncertain parameters that characterize the disassembly process through an acyclic graph that represents quantitative and qualitative information related to the disassembly. They applied it for a computer disassembly to optimize the sequence [13]. Yan and al. [51] combined DL technology and device electrocardiogram (DECG) for RUL estimation and maintenance. On one hand, DECG permits industrial application maintenance to monitor the product cycle and provides predictive data in the product lines improving operator efficiency and non-planned downtime [51]. On the other hand, DL technology has the benefit of extracting features automatically which simplifies prediction for RUL.

Application of Virtual Reality and Artificial Reality.

Virtual reality (VR) and augmented reality (AR) are two technologies of industry 4.0. VR enables the 'virtual disassembly' and 'virtual maintenance' possibilities with simulations and optimization of the physical processes [37]. Qiu and al. [37] proposed an interactive model based on VR that analyses constraints, interaction, and methods of operator assembly and disassembly through 'virtual human' (VH). AR can be defined as the overlaying of virtual signs, icons, or imagery on physical reality [6]. Introduced by Ronald Azuma [5], it can benefit the aviation industry. Ceruti and al. [6] investigated the use of AR and additive manufacturing for the maintenance process. They proposed to use AR to better assist operators in a maintenance process to achieve better efficiency and reduce the possibility of errors. Mo and al. [29] present virtual disassembly through the virtual environment Motive3D. They proposed virtual disassembly analyzer (VDA). VDA uses CAD models' inputs, then proceed to generate a disassembly sequence and assess it with the data deployment tool (DDT). Together, DDT and VDA constitute the server Motive3D that enables the visualization of the disassembly process in 3D. Motive3D shows gesture of operators with special data gloves that shows rotation, movement, translation, grasp, release, mouse movement or selection.

Application of Collaborative robots.

Collaborative robots (CR) or collaborative human-robot (H-R) are programmed to assess, plan, and perform tasks while considering human constraints and the limitations of the environment [21]. Manual disassembly is not optimal from an economic point of view. On the other hand, the use of regular robots is not reliable enough for complex products [35] such as EoL aircraft parts. Parsa and Saadat [35] recommended that the CR can assess the sequence to be disassembled based on remanufacturing potential. The operator will be helpful in difficult tasks considering the required flexibility. Hjorth and al. [14] conduct a literature review on CR for the non-destructive disassembly process of EoL objects. They've highlighted some gaps in the field as the strategies put in place with H-R collaboration are mainly the avoidance of contact with the operator or the lack of a combination of the verbal and the non-verbal communication method between the worker and the CR. Ottogalli and al. assessed with VR technology the CR in the assembly line of an aircraft because most of the task is executed manually [33]. They developed a framework to assess the process of semi-automation tasks, the return on investment and the ergonomics of the workers. Liu and al. [24] proposed to use of an algorithm to optimize the robotic disassembly sequence with a collaborative H-R in the remanufacturing process.

3.2 Summary of Industry 4.0 technologies in EoL aircraft Problem

Table 1 presents 7 technologies of industry 4.0 and their implications in EoL aircraft, how those technologies can be used, the related literature and the industry 5.0 perspectives. Industry 5.0 is a new movement that introduces the efficiency and precision of industry 4.0 technologies while integrating the subjectivity and intelligence of humans [23]. Leng and al. [23] discussed that industry 5.0 is driven by three key characteristics: 'Human centricity', sustainability, and resiliency. 'Human centricity' is the principle that humans bring higher levels of tolerance to the systems.

Table 1 - Industry 4.0 technologies and EoL aircraft process

Technologies	Advantages	Processes intervention	How it is used	Literature	Industry 5.0 application
Blockchain	Traceability Visibility Security Information	Maintenance Recovery Remanufacture Recycling Re-using	a. Tracking of aircraft parts b. Maintenance records of aircraft available in real-time c. Smart contract possibilities	[3] [20] [44] [48]	**Sustainability**: clients expect the supplier to deliver sustainability-related information on products. The utilization of blockchain technology as a solution for the absence of traceability in the supply chain. [23]

	Sharing/ac-cessibility		d. Data sharing and monitoring for airworthiness status e. Secure the data		**Resilience:** product life cycle data [23]
IoT	Traceability Accessibility Prediction of comportments	Maintenance Standardized records Sales, and storage	a. Maintenance records of aircraft available in real-time b. Standardization of maintenance record c. Monitoring for airworthiness status	[19] [23] [44] [48]	**Resilience:** internet of everything (IoE) offers new capabilities such as: (a) allowing predictive maintenance operations performed to avoid issues instead of planning once a defect occurs. (b) Combining IoT sensors with DT technology to collect real-world data [26]
Digital Twins	Simulation/ optimization process Accessibility Decentralized Transparency	Simulation Recycle Recovery Remanufacture	a. Real-time simulation for optimization of dismantling or disassembling process for an aircraft b. Diagnostic operational problem c. Can predict scenario	[19] [25] [31] [36] [49]	**Human centricity and resilience:** Society 5.0: merging physical environment with cyberspace. Metaverse: immersion for H-R/CR [23]
Big Data	Simulation/ optimization process Prediction of comportment Reliability/ Accuracy	Predictive maintenance, Recycling Re-using Disassembly Remanufacture	a. Predict maintenance. b. Predict comportments and tendency c. Predict and optimizes for remanufacturing. d. Green maintenance	[9] [19] [28] [55] [57]	Society 5.0: Data-driven society **Resilience characteristic**: mass-personalization [23] BD: Faster decision-making [26]
AI	Simulation/ optimization process Prediction of comportment	Disassembly Remanufacture Recycling	Predict residual life of an aircraft parts	[4] [22]	**Resilience:** 'Better task allocation' [23] 'Better handling of reitative jobs' [23] Manufacturing activities' hyper customization [26]
AR / VR	Reliability Error Minimization Ergonomy	Maintenance Simulation Disassembly Remanufacture	a. More efficient process for disassembly of parts b. Maintenance process optimization	[5] [6] [37]	**Resilience:** extended reality (combination of VR/AR): is used for remote assistance, assembly line monitoring, training, and maintenance [26]
Collaborative robot	Optimization process Productivity Cost prevention Ergonomy	Disassembly Remanufacture	Disassembly of semi-automation process for safety purposes, to be more cost-effective, and productive.	[14] [21] [24] [33] [35]	**'Human centricity' and resilience:** Operator 5.0 / Cobots (collaborative robots): system/self-resiliency, enhancing flexibility and dexterity, analyzing and optimize human work [23,26].

3.3 Evaluation of technologies.

Blockchain permits traceability, reliability, and security but can be complex in the adoption process. IoT also allows for visibility and traceability, although its energy consumption might be a challenge. DT can be combined with AI or used alone to simulate scenarios and optimizes them by mimicking the physical world into a digital world with real-time scenarios. AR/VR helps analyze ergonomically and minimizes errors in certain processes such as disassembly or remanufacturing. CR can optimize operations and add values, but it can be a challenge to integrate into a disassembly chain and to be trustable by operators. Addressing the challenges and opportunities of these technologies in EoL aircraft problem to maximize its value and minimize the negative impact on sustainability is a complex task. To determine which of the technologies of Industry 4.0 will be valuable in the EoL sustainable decommissioning of an aircraft, multi-objective decision-making (MCMD) approach can be applied. One of the most applied MCDM methodologies is the analytics hierarchical process (AHP) which was first introduced by Saaty [42]. This method provides a classification of different alternatives considering qualitative and quantitative information and evaluates the consistency of the results and criteria. The gap in this method is the lack of consideration of the relation between criteria, so Saaty proposed a variation: the analytic network process (ANP) method. The ANP provides a network structure to analyses the alternatives [30]. This method has been used to assess industry 4.0 technologies. Chang, Chang, and Lu [7] used the MCDM approach of ANP and the technology-organization-environment framework (TOE) to assess in small and medium enterprises the utilization of technology 4.0. Ravi and al. combined ANP and the balanced scorecard approach (BS) to classify EoL computers into the reverse logistic context [39]. Ordooadi proposed to consider quality, flexibility, cost, and impact on human resource when considering the adoption of technologies [32]. As already discussed, the importance of traceability features and maintenance reports and requirements is critical in the aerospace industry. Real-time data exchange, security, reliability, certification information, substitutability, energy consumption, environmental impact, social impact, and economic impact, are key criteria to consider when evaluating and classifying the technology alternative in an EoL context. Those airworthiness information needs to be considered when evaluating technologies from industry 4.0.

As shown in Figure 2, this paper presents ANP framework of criteria to evaluate the best options among industry 4.0 technology for EoL aircraft treatment. Four categories of criteria have been considered in the model through the literature: economic, environmental, and social, for the triple bottom line and the technological performance (level 1). Sub criteria related to the aerospace industry are considered in the level 2. In level 3 the preliminary indicators are presented and will be used when evaluating the different alternatives (level 4).

Conclusion

Valorization of EoL aircraft is an important research field considering the 20 000 aircrafts that will be decommissioned in the next 20 years. The aerospace industry focuses on maximizing the value of those EoL airplanes that are often just parked in desert. For successful operation of reused and remanufactured parts, the reliability of the components, ease of disassembling, inspection, cleaning, and maintenance data should be considered. Industry 4.0 tools provide several opportunities with analyzing real-time data and facilitate the decision-making process The blockchain technology, the Internet of Things, digital twins, big data, artificial intelligence, augmented reality/virtual reality, and collaborative robots are discussed. An MCDM based framework is proposed to assess and classify those technologies with the analytical network process. As the future research, secondary data from EoL aircraft treatment of a pilot project will be used to assess the impacts of Industry 4.0 in the different sub-processes of EoL aircraft treatment based on waste hierarchy approach. Moreover, the preliminary ANP model in this paper will be completed, readiness of the alternatives will be added as a key factor and applied in a real case study.

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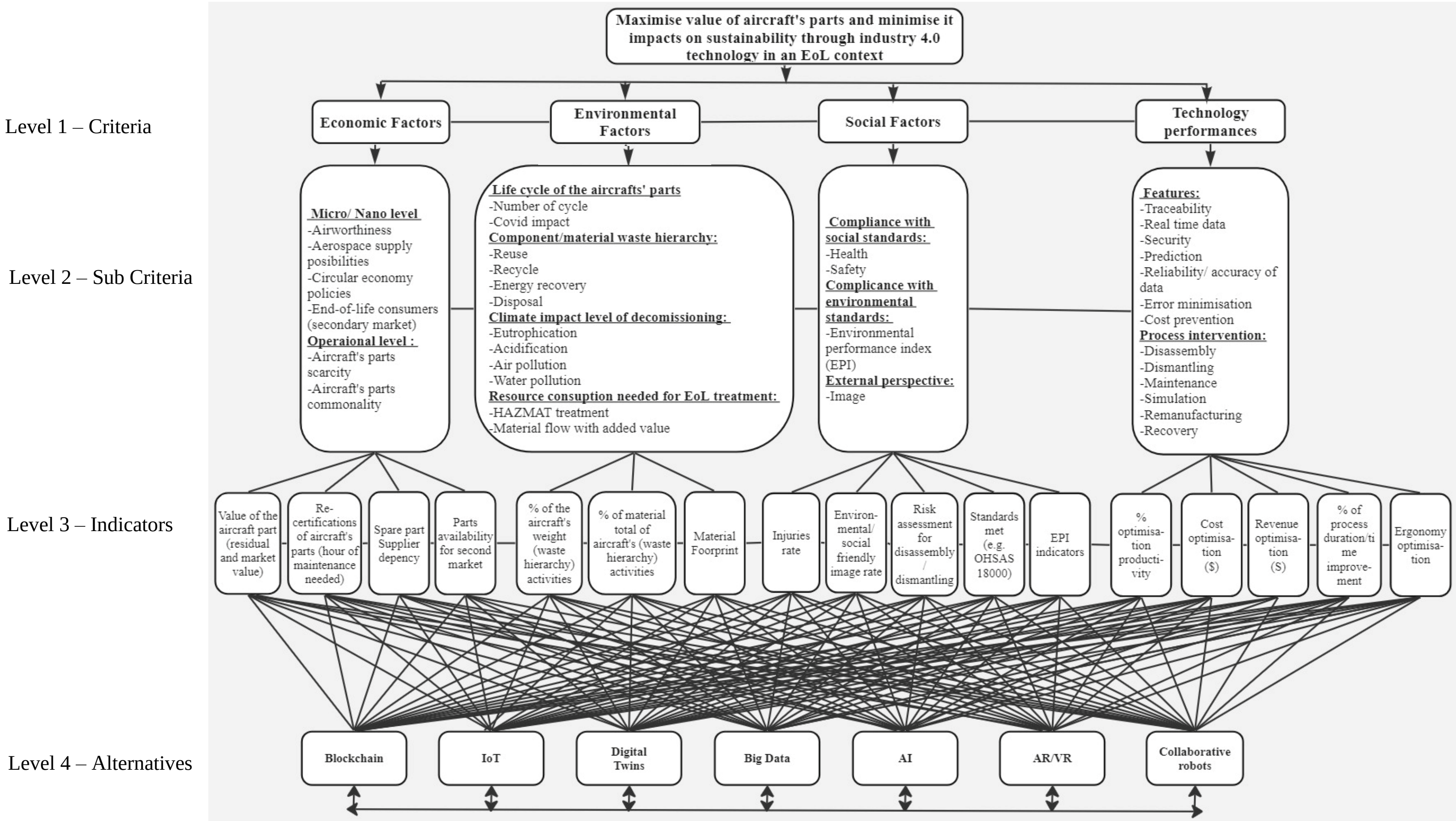

Figure 2 - ANP model for the technology of industry 4.0 to decommission an aircraft

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