ON THE ADOPTION OF CIRCULAR ECONOMY CONCEPTS IN THE MANUFACTURING SECTOR

by

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Declaration of Authorship

I declare that this thesis is my own work and, to the best of my knowledge and belief, it does not contain material published or written by a third party, except where permission has been obtained and/or appropriately cited through full and accurate referencing.

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Dedication

To my family

Thank you for your unlimited support for which I will be forever grateful!

To my father, Mr. Alaa Ahmed

Words cannot express how thankful I am for all the support and knowledge you have provided me with since day one! I am more grateful to you than you'll ever know.

Abstract

Industrialization has brought wealth, prosperity, and abundance to many nations. However, it has had many drawbacks on people's health and the environment. Several paradigms have been proposed and implemented in an effort to suppress and reverse the adverse impacts of human activities and industrialization. A popular approach is the circular economy (CE). CE is a waste conservative model that limits resources uptake, waste generation and energy consumption. The implementation of today's top-notch technologies such as Industry 4.0 tools is a necessity to enable the transition from the conventional linear economy to the CE. Moreover, to ease this transition, it is important to be able to assess the circularity of different products and processes along the way. Most available assessment procedures lack comprehensiveness and objectivity due to complexities such as the quantification processes of qualitative data, the extensive use of linguistic terms that represent data and the uncertainties associated with them, and the difficulty in combining more than one indicator in case of similarity, dependency, or both. The aim of this thesis is to firstly present a thorough review on the applications of cyber-physical systems within each of the CE stages and highlight their contribution to the attainment of the different sustainable development goals through several practical examples. Secondly, it presents a comprehensive CE assessment framework that can assess the circularity of developed and developing countries, different industries, wide range of processes, and different products, of both private and public sectors on a micro, meso, and macro levels. This is achieved through a step-by-step indicators selection procedure and the combination of fuzzy logic and multi-criteria decision-making methods which deliver a CE assessment that eliminates previously mentioned problems and result in an unbiased realistic ranking of alternatives. The presented framework is implemented to assess the circularity of Friction Stir Back Extrusion against conventional extrusion methods. Results show a higher circularity score for the FSBE (48.9%) over conventional extrusion methods (4.78%), validating the applicability of the proposed CE assessment framework.

Keywords: Circular economy; Cyber-physical systems; Industry 4.0; Sustainable development goals; Fuzzy logic; Multi-Criteria Decision-Making (MCDM) Methods; Sustainable Development; Sustainability.

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List of Abbreviations

ACA	Ant Colony Algorithm
AHP	Analytical Hierarchy Process
AI	Artificial Intelligence
ANP	Analytical Network Process
ANZSIC	Australian New Zealand Standard Industrial Classification
AR	Augmented Reality
AVGs	Autonomous Guided Vehicles
CE	Circular Economy
CM	Circular Manufacturing
CNN	Convolutional Neural Network
COG	Centre of Gravity
COPRAS	Complex Proportional Assessment Method
CPMAS	Cyber-Physical Multi-Agent System
CPPSs	Cyber-Physical Production Systems
CPSs	Cyber-Physical Systems
DFMA	Design for Manufacturing and Assembly
EEE	Electrical and Electronic Equipment
FBG	Fibre Bragg Granting
FIS	Fuzzy Inference Systems
FSBE	Friction Stir Back Extrusion
GHG	Greenhouse Gas Emissions
GRA	Grey Relational Analysis

I4.0	Industry 4.0
IoT	Internet of Things
KPIs	Key Performance Indicators
MCDM	Multi-Criteria Decision-Making Methods
MFs	Membership Functions
MSW	Municipal Solid Gas
NACE	Statistical Classification of Economic Activities in the European
NAICS	North American Industry Classification System
NASA	National Aeronautics and Space Administration
QA	Quality Assurance
QC	Quality Control
R&D	Research and Development
RIFD	Radio Frequency Identification
SD	Sustainable Development
SDGs	Sustainable Development Goals
SNI	Swedish Standard Industrial Classification
TOPSIS	Technique for Order Preference by Similarity to the Ideal
UKSIC	United Kingdom Standard Industrial Classification of Economic Activities
UNSPSC	United Nations Standard Products and Services Codes
USA	United States of America
VR	Virtual Reality
WEEE	Waste Electrical and Electronic Equipment
WNDM	Weighted Normalized Decision Matrix

Chapter 1. Introduction

1.1. Introduction

This chapter provides a brief introduction about the concept of circular economy (CE) and its significance in the contribution to the attainment of the Paris agreement and the sustainable development goals (SDGs) set by the United Nations (UN). This will be followed by two sections highlighting firstly, the thesis objective, secondly, the research contribution. While the last section of this chapter will present the thesis organization.

1.2. Overview

The world's population has drastically increased over the course of the past few decades. It is estimated that the population will reach 8.5 billion by 2030 and 10.9 billion by 2100 [1]. Subsequently, this fast-paced population growth contributes to a substantial increase in energy demand and consumption. Energy consumption is projected to increase by 50%, reaching approximately 900 quadrillion British thermal units (Btu) by 2050 as seen in Figure 1 [2].

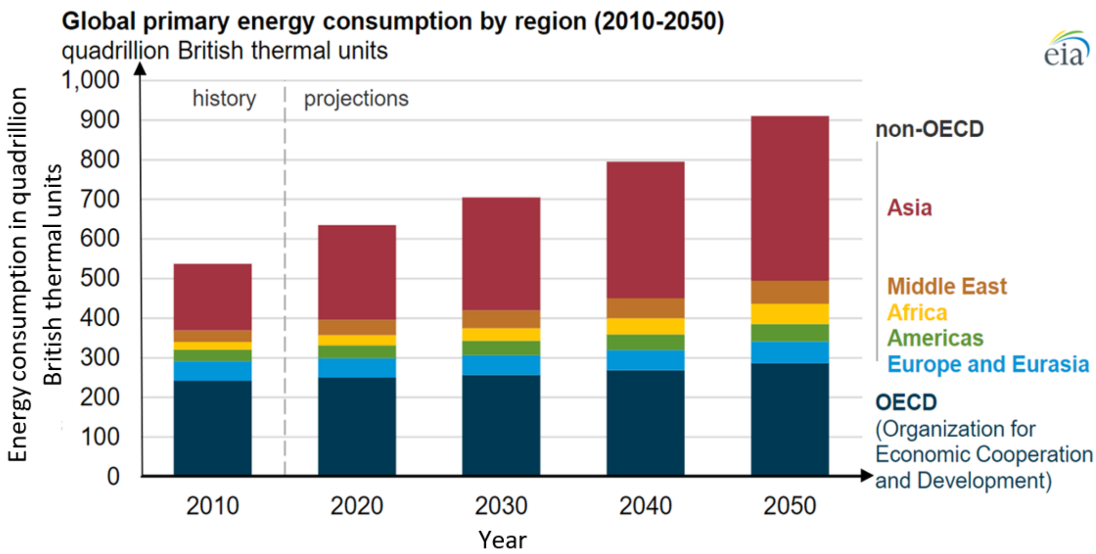

Figure 1: Global primary energy consumption by world region in 2019 [2]

Human activities have caused an estimated 1.0°C of global warming above pre-industrial levels [3]. The concentration of CO_2 in the atmosphere has been increasing since industrialization. Countries such as China, India and the USA attract most of the global industries, which explains the huge amount of CO_2 produced by these nations as seen in Figure 2. This slight increase in the Earth's temperature has melted ice caps causing extreme weather conditions and changed rainfall patterns across the globe [4].

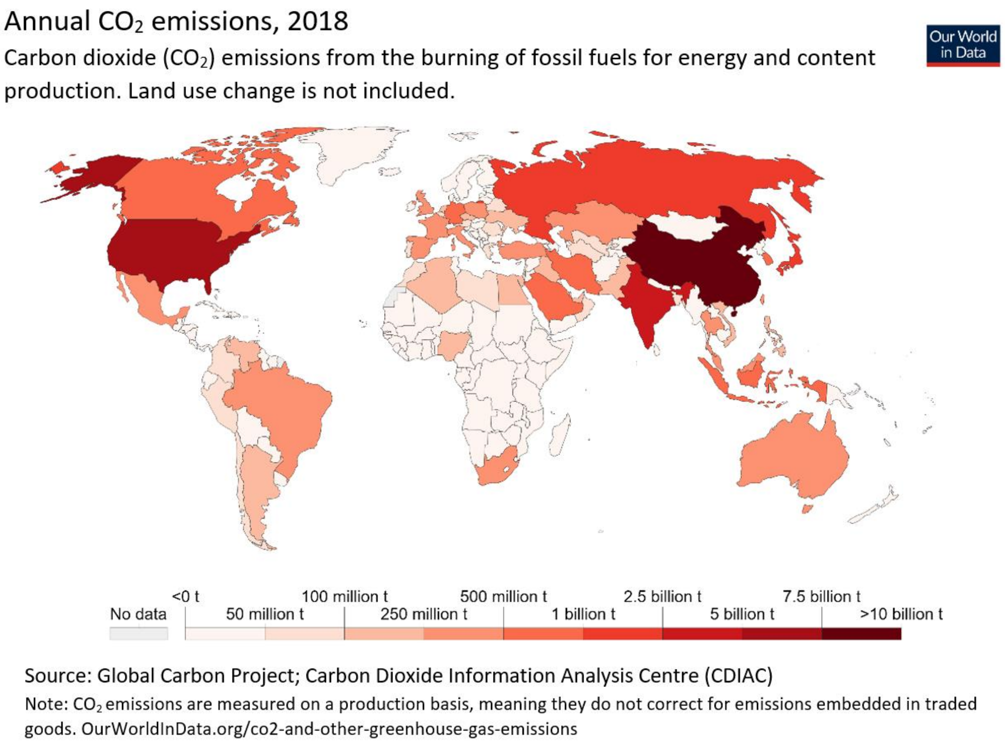

Figure 2: Annual CO2 emissions in 2018 by country [4]

In general, energy used in the industrial sector was responsible for about 24.4% of the global greenhouse gas (GHG) emissions in 2016. It is followed by transportation accounting for 16.2% [5]. Global warming can cause floods in some places and extreme drought in other places. It threatens marine life and biodiversity, leads to deterioration of food security situations, and causes population displacement [6].

Another problem associated with industrialization and human activities is waste generation. In 2018, the USA landfilled about 146.2 million tons of municipal solid waste (MSW). Food waste accounted for the largest portion with about 24% of the total waste followed by plastics, paper, and paperboard [7].

One of the most prominent strategies to limit and reverse the severe effects of climate change and the impacts of waste accumulation is the adoption of a circular economy (CE). In the traditional "one-way" or in other words, "linear" manufacturing model, raw materials are used to manufacture goods that are sold, used, and then discarded as waste to landfills [8]. Environmental benign manufacturing processes and systems have been adopted to reduce the impact of manufacturing on environment [9]-[34]. However, more efforts are needed to combat climate change and preserve resources.

In contrast, the CE model is a waste conservative model that is defined as "*An Industrial system that is restorative or regenerative by intention and design"* [35]. CE focuses on achieving prosperous economic development while protecting the environment by saving resources through recycling. It also takes social aspects into consideration [36, 37]. Similarly, the United Nations defined sustainable development (SD) as "meeting the needs of the present without compromising the ability of future generations to meet their own needs" [38]. In 2002, economic development, social development and environmental protection were defined during the World Summit on SD as the three main sustainability pillars [39]. Since both CE and SD share the same goals, CE could be defined as a condition for SD in general [40, 41, 42]. Studies suggest that the transition to CE and its implementation in the manufacturing industry would contribute to the making of new business opportunities as well as representing a new sustainable growth path [37]. Consequently, CE practices can potentially save around 80% to 90% of raw materials and energy consumption when compared to the linear model [43]. Economically speaking, CE practices can potentially cut product costs by 25% to 30% [43]. An optimistic study revealed that the implementation of CE practices in Europe could have an annual benefit of around 1.8 trillion Euros by 2030 [44]. Correspondingly, the rise in the demand of sustainable products driven by the reduced prices would create more job opportunities in the sustainable sector [45]. These promising figures have caused many countries, such as China, Japan, Canada, the United States and Brazil, to aim at attaining sustainable development goals (SDGs) by implementing CE across their different industries and sectors [46].

1.3. Thesis Objectives

Driven by the urgent need to decrease resources uptake and waste generation, and to significantly lower our greenhouse gases emissions, the main objective of this thesis is to present innovative solutions that facilitates and eases the world's transition from linear to circular economies. Firstly, this thesis will focus on presenting models and solutions based on industry 4.0 to enable a smooth CE transition that aims to achieve the different SDGs set by the UN. Moreover, it will focus on developing a comprehensive multi-level CE assessment framework and tool that is capable of assessing the circularity of different products, companies, industries or even countries using subjective and objective means of assessment. Moreover, it can point out areas of improvement towards circularity. This thesis will focus in incorporating artificial intelligence in the form of fuzzy logic to ease the quantification process and promote autonomy to reduce errors and subjectivity as well as provide users with reliable and realistic results.

1.4. Research Contribution

The contributions of this research work can be summarized as follows:

- Presented a thorough review on the implementation and integration of CPSs in each of the CE stages, highlights the SDGs that would be achieved as a result.
- Developed a novel illustrative House of Sustainability that summarizes the relationship between sustainable development (SD), Circular economy (CE), Industry 4.0 (I4.0), and the Sustainable development goals (SDGs).
- Presented a review on the current state of the CE assessment tools.
- Developed a comprehensive multi-level circular economy assessment framework that can be used for private and public sectors.
- Developed a first of a kind AI – fuzzy logic enabled CE assessment tool that promotes autonomy and reduce errors.
- Compared the circularity of conventional extrusion methods to friction stir back extrusion (FSBE).

1.5. Thesis Organization

The following sections of the thesis are organized as follow: Chapter 2 presents a review on the role of the implementation of an important I4.0 tool, CPSs, in the enabling of CE. This is carried out by discussing each stage of the CE separate sections throughout the chapter. Moreover, the chapter shows how the implementation of CPSs within each stage contributes to the attainment of different SDGs. Finally, the chapter highlights the need of a CE assessment tool. This assessment tool is developed and discussed in detail in Chapter 3. The implementation of the developed framework is carried out in Chapter 4. Finally, Chapter 5 concludes the thesis and summarizes the future work.

Chapter 2. Cyber-Physical Systems as an Enabler of Circular Economy to Achieve Sustainable Development Goals: A Comprehensive Review

This chapter presents a thorough review on the applications of cyber-physical systems within each of the CE stages, the contribution of different CPS technologies to the sustainable development goals (SDGs), and the current state of the CE assessment tools. The contribution of different CPS tools to each CE stage is demonstrated through several practical examples. In addition, this work reveals how the different CPS technologies applications contribute to the attainment of different SDGs set by the United Nations. Lastly, it highlights the need of a comprehensive CE assessment tool through a literature review on the available frameworks.

2.1. Circular Economy

A general CE model is presented in Figure 3. CE can be divided into five stages with design and transportation being a common interconnecting stage among all the individual stages. The five stages are: sourcing, manufacturing, distribution, use, and recovery. However, this paper will include design as a stage which is in place prior to manufacturing. Each stage plays an important role in keeping the model circular; “leakages” in any of the stages cause a discontinuity, defeating the purpose of the circular paradigm. Over the past few years, the implementation of the CE paradigm throughout industries has led to the emergence of new supporting technologies that have eased the adoption of sustainable manufacturing measures into the CE cycle. This type of manufacturing is known as circular manufacturing (CM) [42].

Similarly, different stages in the economy need to undergo technological updates to ease their transformation from a linear economy to a CE. There has always been a need to develop all outdated technologies into smart ones. Machines are now required to understand and interpret the physical world and to perform tasks flawlessly for better service. For that to happen, there should be a system that would obtain information from the physical world and translate it in a way that can be understood by machines in their cyber world. Fortunately, these types of systems exist and are called cyber-physical systems (CPSs). In general, Industry 4.0 (I4.0) tools, such as CPSs, the Internet of things (IoT), augmented reality, big data, simulation, autonomous robots, cloud computing, additive manufacturing, cyber-security, and artificial intelligence can be key enablers for CE. Several papers joined more than one I4.0 tools together to increase the capabilities of different processes. For example, dyeing processes were updated to save energy using different I4.0 tools [47]. Another paper reviewed smart machining processes using machine learning [48].

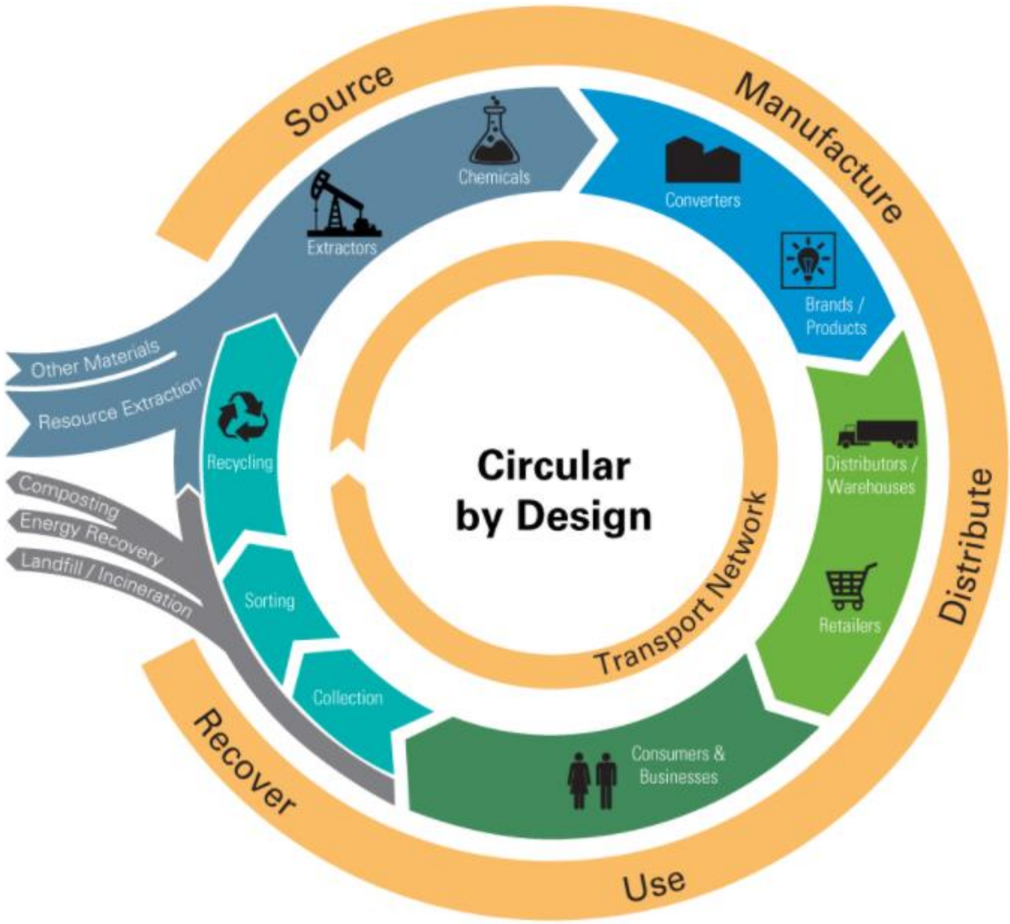

Figure 3: A general circular economy (CE) model [49]

2.2. House of Sustainability

The shared goals of the confluence and integration of CE and I4.0 can be illustrated using the House of Sustainability shown in Figure 4. People are considered the foundation of the sustainability house, while the purpose is what drives people towards their goals. The incorporation of different I4.0 tools within the CE builds a strong support that different SDGs can lean on. These goals are the building blocks of sustainable development (SD). Together, they achieve different attributes of the three pillars of SD: environmental, economic, and social. The House of Sustainability provides a clear picture of how I4.0 and CE complement each other. Without the supporting I4.0 tools, CE is not sufficient to achieve SD. Similarly, incorporating I4.0 tools into a linear economy will not achieve SD.

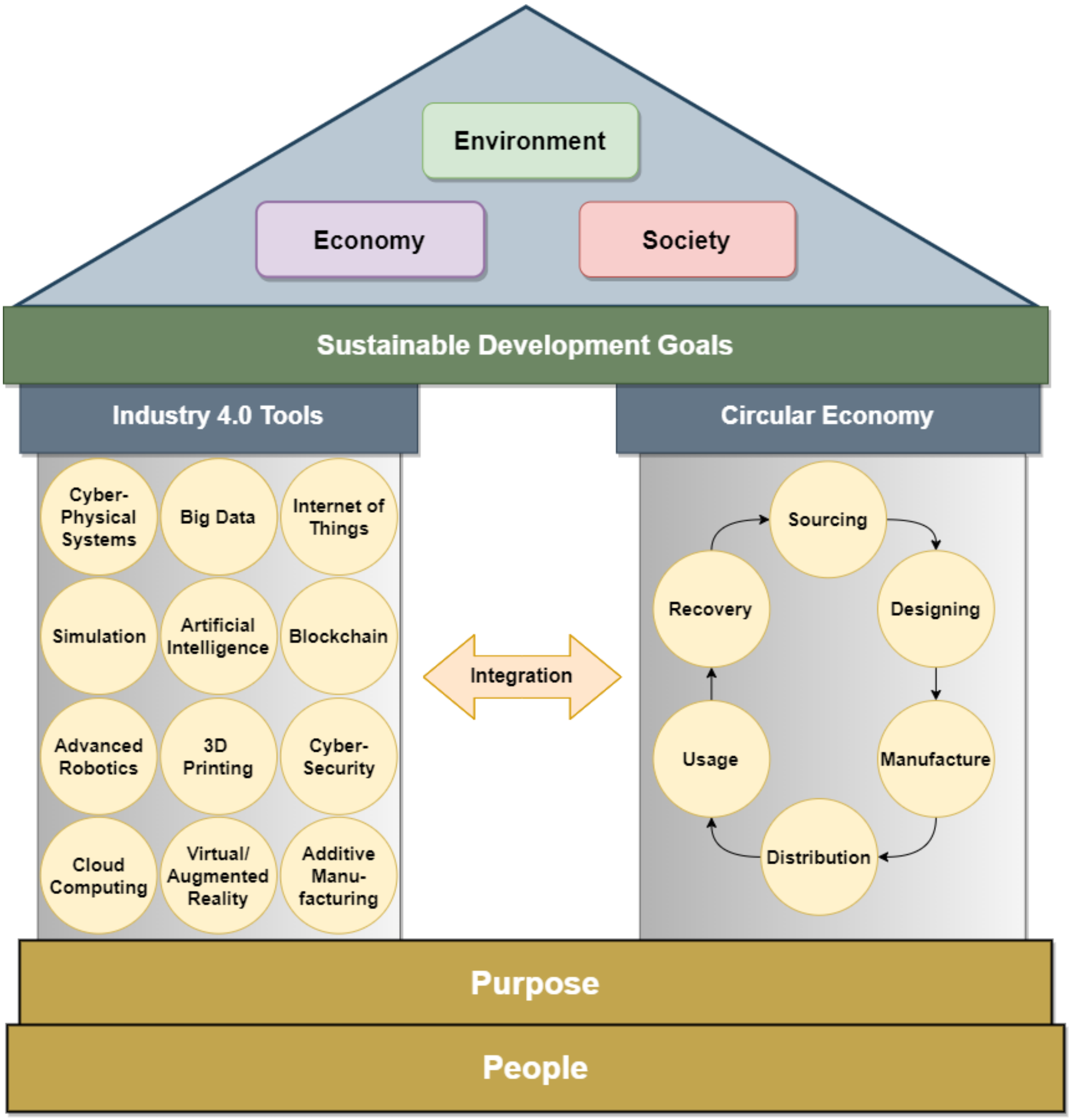

Figure 4: House of Sustainability

2.3. Literature Review

Several papers review the implementation of I4.0 tools in the CE. Very few however link the integration of I4.0 technological tools into the CE to the achievement of SDGs. Almost none present a comprehensive review in terms of the CE stages while linking them to the possible SDGs achieved. Table 1 presents different review papers that directly mentions the implementation of different I4.0 tools into the CE. The table presents the I4.0 tools mentioned in the review papers, the CE stages targeted, and the SDGs achieved if any.

Firstly, Kerin and Pham [50] reviewed the literature on the emerging digital technologies of I4.0 in remanufacturing. As a conclusion, it was found that such an implementation of I4.0 technologies, mainly IoT, VR and AR, contribute to the achievement of goals 9.4 and 12.5 of the SDGs. A similar approach was illustrated by Dantas et al. [51] in a paper that presented a review on how the combination of CE and I4.0 contributes towards achieving different SDGs. The authors reviewed papers in terms of CE practices and not CE stages. As a result, some stages were missed such as the sourcing and the usage stages. Out of the 50 papers reviewed, 42 directly addressed a CE practice, and 17 out of these 42 papers discussed an I4.0 tool.

Generally, the authors did not capture all CE stages due to the nature of the review that focuses on CE practices rather than CE stages individually. On the other hand, Gupta, Kumar and Wasan [52] presented a range of I4.0 technologies implemented on 3 CE stages which are the manufacturing, usage, and recycling stages. However, SDGs were not covered in the review. Moreover, Leng et al. [53] reviewed different aspects of the manufacturing stage focusing on blockchain technologies individually, with no reference to the SDGs achieved. Sarc et al. [54] also reviewed the implementation of various I4.0 technologies in waste management but without including SDGs in the review. Another review by Khan Ahmad, and Majava [55] mapped I4.0 to CE and sustainable business model perspectives.

However, CE was discussed from the implementation perspective and not from stages point of view. Also, SDGs were not discussed in this review. Overall, it can be clearly noticed that reviews focusing on the implementation of I4.0 tools in the CE fail to capture either all CE stages or does not incorporate SDGs. Due to the vast amount of I4.0 present, it is very hard to capture how the implementation of these technologies in different CE stages achieve different SDGs. Hence, to present a novel review on the topic, this paper reviews possible ways the integration of one I4.0 tool, the cyber-physical systems (CPSs), into each of the CE stages facilitates the achievement of different SDGs. Also, it highlights the need of a comprehensive CE assessment tool, and reviews some of the tools presented in the field and literature.

Table 1: List of review papers on the implementation of I4.0 in CE

Source	Industry 4.0 Tool	CE Stage	SDGs
Kerin and Pham [50]	AI, AM, AR, VR, IoT	Manufacturing	9.4, 12.5
Sarc et al. [54].	IoT, CPSs, Blockchain, AI	Recycling (Waste Management)	Not Included
Dantas et al. [51]	AM, AI, Blockchain, IoT, Simulation, CPSs, Cybersecurity, AR	CE Practices in: Design, Manufacturing, Distribution, Recycling	7, 8, 9, 11, 12, 13
Gupta, Kumar, and Wasan [52]	IoT, Bigdata, Smart factory, Cloud computing, AM, CPSs	Manufacturing, Usage, Recycling	Not Included
Leng et al. [54]	Blockchain	Manufacturing	Not Included
Khan, Ahmad, and Majava [55]	I4.0-based technologies	CE implementations: Smart cities/factories, supply chains	Not Included

2.4. Cyber-Physical Systems

As Figure 5 illustrates, CPSs can be defined as systems that "consist of computation, communication and control components tightly combined with physical processes of different domains such as mechanical, electrical, and chemical" [56]. CPSs enhance the potential of physical systems by interacting with physical processes using deeply embedded computations and communications that control and monitor physical processes through feedback loops. This allows physical processes to affect computations and vice versa [57]. In other words, CPSs provide a real time linkage between humans and physical or production systems. This linkage is created using sensors, actuators, and computers through a network [58].

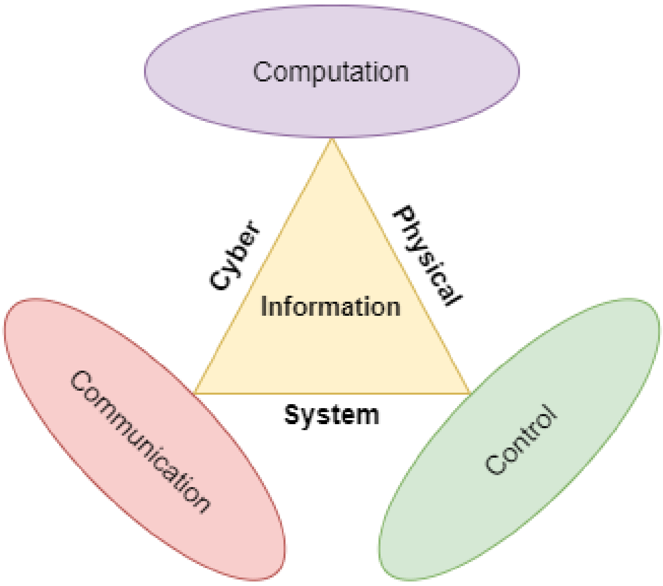

Figure 5: Cyber-physical system (CPS) components [59]

There are six main components needed to fully develop CPSs. These components are sensors and actuators that are used to interact with the physical world; a power supply, as well as analog and digital hardware components, such as power electronics and digital convertors, respectively, a network; and lastly, the heterogeneous software microprocessors or microcontrollers that are used for software execution. Due to their flexibility, CPS technologies define the newest ongoing industrial revolution by their enormous application domains. Such applications include but are not limited to communications, consumer services, energy, infrastructure, healthcare, manufacturing, robotics, military, and transportation.

Throughout the literature, authors often discuss IoT and CPSs as interchangeable concepts. This is due to the overlap between these two concepts. IoT is when the "*virtual world of information technology integrates seamlessly with the real world of things*" [60]. Moreover, IoT involves three main steps that occur iteratively in the following order: sensing, thinking, and acting [61]. The aforementioned points apply to CPSs as well. However, the major difference between these two concepts is the use of the internet. The IoT relies on the internet to link between the virtual and the physical worlds. In contrast, CPSs can use either the internet or a feedback loop. Hence, it is safe to say that IoT is a special class of CPS that only uses the internet. However, since this is debatable, this paper will focus mainly on CPSs using feedback loops with only some examples requiring a minimum use of the internet.

The CE paradigm is presented as a solution to tackle previously mentioned drawbacks of human activities in general and industrialization in particular. Moreover, I4.0 describes an innovative manufacturing path that transforms conventional manufacturing to a more sustainable and conservative model by utilizing different technological tools. Both concepts were coined separately on different occasions but due to their shared goals, many papers [62, 63, 64, 65, 66, 67] have connected I4.0 to CE. As of yet, no one has established a comprehensive connection among and between all CE stages with a specific I4.0 tool. Instead, they have focused on only one stage, mainly manufacturing or logistics, while keeping the rest of the CE model unchanged. In contrast to the conventional CE model, which does not include I4.0 tools, this paper presents an up-to-date version of the CE paradigm that exhibits how sustainability can be achieved across different CE stages by implementing one of the most important I4.0 enablers, CPSs. This is presented by highlighting how CPSs impact each stage of the CE. In addition, the relevant SDGs that are achieved through the CPS enabled CE are revealed and discussed.

2.5. Intra-Impact

This section discusses how CPSs can be embedded into each stage of the CE model. This highlights the potential of CPSs for enhancing each stage of the CE in terms of efficiency and sustainability.

2.5.1 Sourcing

Sourcing is the first stage of the CE. Most of the raw materials needed by manufacturers are obtained through the use of different extraction processes in the sourcing stage. The main challenges faced in this stage are the excessive exhaustion of raw materials, the environmental impact, as well as the health risks involved in the extraction process. The implementation of different I4.0 enablers, such as IoT and big data, play an important role when it comes to the optimization of resources and decision-making processes. However, this section will present how CPSs alone could impact resource mining.

2.5.1.1. Autonomous mining operations

CPSs can be harnessed to tackle health risks posed during mining and other methods of extracting resources. For example, toxic levels of arsenic present in gold mining areas in the Amazon pose health risks to miners and locals [68]. To reduce human exposure to arsenic, CPSs could be implemented to automate some of the mining tasks. In his paper, Wang et al. [69] presented the Human-Robot collaborative assembly. This system was originally proposed for manufacturing facilities. With minor modifications, the Human-Robots assembly can be employed and directed throughout dangerous mining processes, thus creating a safer working environment, and reducing the hazards that the miners are exposed to. It also provides an equal opportunity for laborers since physical work would be minimal as the operation of such robots is relatively easy.

2.5.2 Design

Constant design improvements and a tailored customer experience are the new focus of many industries [70]. For these reasons, it was essential to allocate I4.0 tools in the design of products. CPSs can be used extensively to aid designers by providing them with data that can be used in predicting their design performances or by presenting different designs using previous knowledge.

2.5.2.1. Design information feedback system

One of the most promising of the proposed approaches for the enhancement of product designs is through “the information feedback, provided through CPSs within production facilities” [71]. In this approach, data gathered in the production phase is transformed into usable knowledge for design improvement. Figure 6 presents an approach which begins with sensors and ends with design rules. To explain further, the authors’ approach is to use CPS sensors to gather data which is then classified so that weaknesses or failures within the process can be identified. Hence, CPSs can provide information about irregularities in the process as well as distinct failure states. Through the use of a knowledge base that contains an existing correlation between failure and cause, a reported failure state and its root causes can be deduced. The cause is then assigned to the feature responsible for the cause through another knowledge base. Created by engineers and designers, the last knowledge base provides information on how to avoid detected failures throughout the process of production.

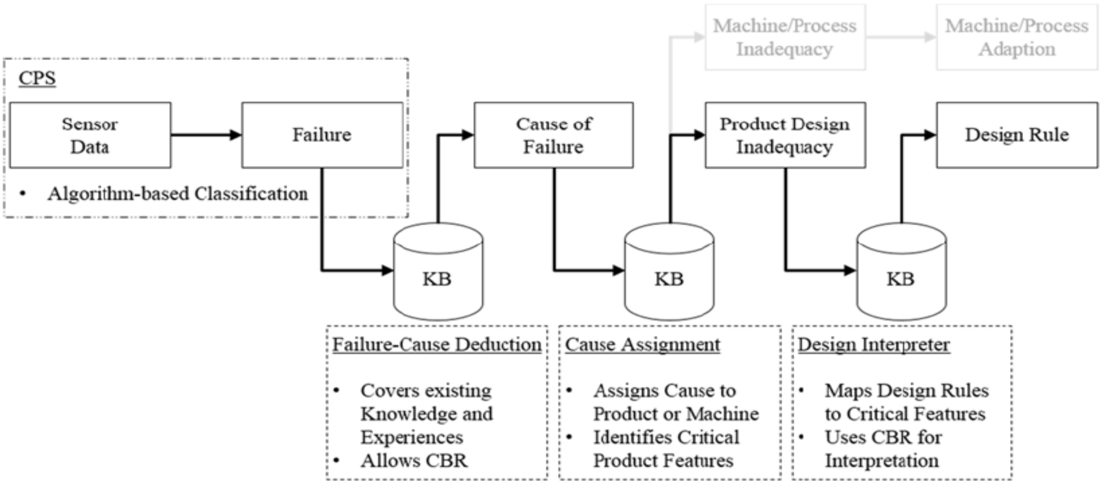

Figure 6: Knowledge feedback to a design process via CPS [71]

2.5.2.2. Testing and simulation assistance in product design

It is important for designers to be able to test their designs before they are produced. For this reason, it is necessary to develop testing and simulation equipment and procedures that accomplish this task in the safest, cheapest, and most timely fashion. Well-known aircraft testing platforms were made possible by CPSs. One of these platforms is the wind-tunnel, which is a widely employed technique used for testing full or scale model components and guides detailed design decisions in thermal-fluid systems [72]. There are various types of wind tunnels, each equipped with a different set of sensors for obtaining data. For example, climate tunnels, which are used to simulate different environmental conditions, are equipped with different sensors than those of smoke tunnels, which are used for flow visualization. Stability tunnels, which are used to study flight dynamics, require different sensors than icing tunnels, which study the effects of ice formation on aircraft wings [72]. A knowledge of the forces exerted on aircraft bodies is critical to aerospace designs; hence, piezoelectric sensors are attached to the aircraft body to measure the dynamic and the quasi-static forces exerted on the aircraft body at different locations.

Moreover, acoustic pressure microphones are used to measure dynamic and acoustic pressure in aircraft and rocket applications [73]. These sensors, along with cameras, angle encoders, motors and other components are illustrated in Figure 7. They equip designers with valuable and critical data without the need to implement a test on the actual aircraft; instead, a scaled model is used. This cuts down the costs and eliminates different hazards caused by design failures.

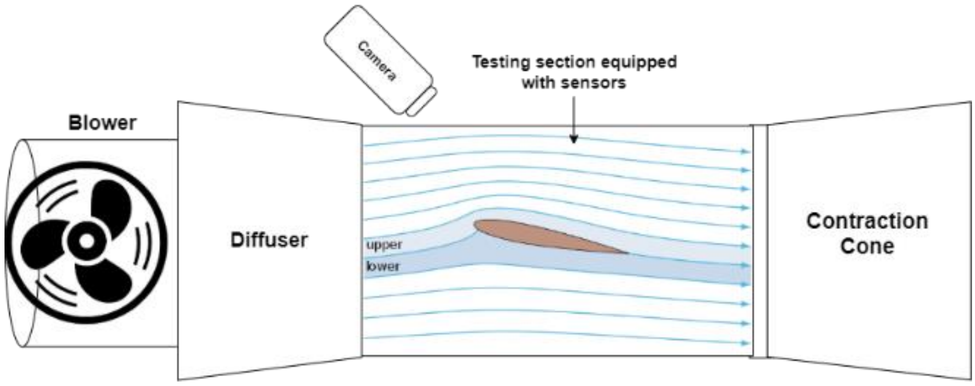

Figure 7: Wind tunnel equipped with cameras and sensors representing a CPS

2.5.2.3. Design for manufacturing and assembly

Design for manufacturing and assembly (DFMA) is a method of designing products that aims to ease the manufacturability and assembly of the components of the product. The main aim of DFMS is to reduce the materials used and the labor costs, which in return reduces the overall costs of the product assembly and the production. CPSs can assist with the decisions made by the designers. As seen in Figure 8, the manufacturing for assembly (MFA) procedure is carried out in five main steps. Firstly, designers work on reducing the number of parts required for the initial design. Secondly, the required or practical parts are determined and counted. Afterwards, the overall product quality is determined based on the product requirements. In the next step, the designers determine the proper assembly methods. Lastly, the design is finalized and executed for production. During the aforementioned process, many decisions are made by the designers. These decisions are based on specific criteria, constraints, material properties, and other considerations. This process would require lots of planning time, and would result in human errors, production costs for any faulty designs, and the operating time for the machines. To avoid this, an architecture similar to the "design information feedback system" could be utilized, in which data presented in the "Knowledge" section of Figure 8 is interpreted by CPSs consisting of software applications, embedded sensors, and feedback loops. The CPSs then make a series of decisions, which include the following: identifying parts that can be standardized; identifying quality opportunities where quality could be compromised if possible; identifying handling opportunities based on the availability of machines and assembly lines; identifying insertion opportunities; identifying opportunities to reduce secondary operations, such as welding; and finally, analyzing data to present the new design.

These decisions are then presented to the designers for a final decision. As a result, manufacturers save substantially on costs that were previously spent on product design [74, 75].

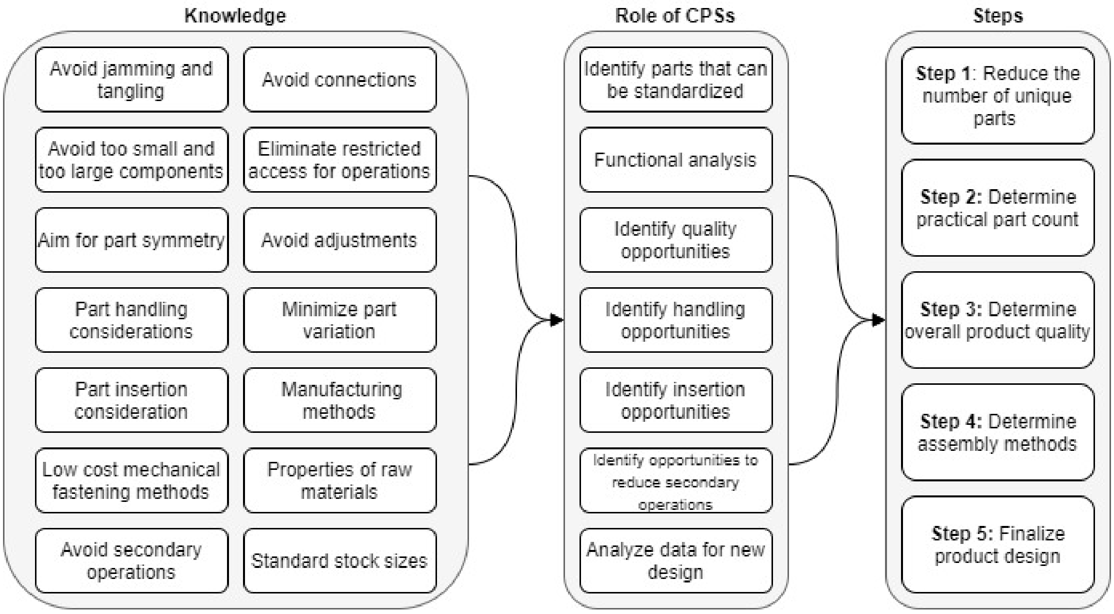

Figure 8: Design for manufacturing and assembling the CPS

2.5.3 Manufacturing

Manufacturing is an integral part of CPSs; for example, the integration of CPSs in manufacturing produces cyber-physical production systems (CPPSs). These systems combine the advancements in communication and information technologies as well as those in computer science with advances in manufacturing science technology and the integration of production logistics [56]. In other words, "CPPSs consist of autonomous and cooperative elements and sub-systems that are connected based on the context within and across all levels of production, from processes through machines up to production and logistics networks" [76]. The use of CPSs could solve many critical challenges in manufacturing, such as quality control, defect prediction, energy consumption, machine health monitoring, and the increasing need for direct human – machine collaboration and most importantly the making of smart factories [77, 78, 79].

2.5.3.1. Quality control and quality assurance

Quality control (QC) and quality assurance (QA) are procedures carried out by manufacturers on their products and processes respectively to ensure adherence to standards and quality criteria, and to meet the requirements of customers and clients.

Internally, manufacturers should assess the quality of their product after each stage preventing defective products from passing into the next stage. Lee et al. [80] proposed an “architecture framework to implement the CPPSs cooperating with other manufacturing information systems for quality prediction and operation control in metal-casting processes” [80]. For example, engine pistons are made from aluminum that is firstly heated and melted inside a furnace where additional elements are added to form an alloy. The molten alloy is then injected into a casting machine where it undergoes cooling and solidification and is transformed into a cast. This is followed by other stages, such as heat and surface treatments, machining and finally, assembly. To save time and prevent unnecessary machine operation hours, CPSs could be implemented to detect defects after each stage to automatically prevent defective products from going onto the next stage using machine vision [81]. According to Lee et al. [80], the main product defects in the aforementioned manufacturing process are generated in the metal casting process where more than 90% of these defects are due to cold shuts and bubbles. Knowing that these defects are mainly caused by temperature variations throughout the process, the authors proposed a CPS consisting of a K-type thermocouple sensor attached to the mold and connected to the controllers to collect the temperature of the casting process, combined with a programmable logic controller that collects other operational data, such as the time taken for the casting process to be completed. Data collected over a period of time was processed using a series of software that was able to achieve a defect prediction rate of 90% and reduce the total monthly operating hours by 18.5%.

Externally, products are either tested individually or in batches after reaching the final form depending on their applications. Highly sophisticated products that have critical applications are usually tested individually to prevent any failures due to manufacturing faults and defects throughout its life span. For this reason, testing strategies similar to those of the wind tunnel highlighted earlier are used. However, due to the high cost of this technique and its very low efficiency in mass production testing, other forms are being implemented that provide autonomous testing and elimination of defective products. Another strategy is product health monitoring, which will be highlighted in section 2.5.3.3.

2.5.3.2. Quality control and quality assurance

Machine health monitoring in manufacturing facilities is essential for quality assurance and accuracy of the manufacturing parts [82]. Any unpredicted or sudden breakage of tools may cause a huge disturbance along the production line. Caggiano et al. [83] proposed a cloud-based CPS architecture for machine smart monitoring that aims to detect tool wear and tool breakage. Such systems can be divided into a cyber-physical based part and a cloud-based part, which will be discussed in a later section. The cyber-physical part consists of the physical machines including the tools used and the sensors. These sensors are usually dynamometers for measuring forces, accelerometers for measuring vibrations, electric current sensors, etc. These sensors are fitted to capture information for tool condition monitoring, such as the lathe-mounted multiple sensor system used for turning process monitoring [83]. Tool wear can be recognized by accelerometers that detect the increasing amplitude of vibrations that is caused by the accumulation of tool wear. Moreover, tool breakage can be also detected using an accelerometer attached at the tool shank, which has been proven to be the most suitable place for the sensor attachment. The accelerometer is very sensitive and could easily detect a change in the contact between the tool tip and work piece. A similar approach by Villalonga et al. [83] includes the design of a condition-based monitoring architecture for CNC machine tools. This approach provides solutions to monitor the machine's elements and components and predicts failure patterns during the life cycle of the machine tool.

2.5.3.3. Product health monitoring

Product maintenance is one of the key factors to increasing the life span of any product. Automotive manufacturers set fixed time intervals for customers to bring in their cars for maintenance regardless of the condition of the car. This is considered a safety measure that is not only implemented in the automotive industry but also in the aerospace industry. Health monitoring of aircrafts is very critical and directly contributes to the safety of air travel. Yet many accidents occur due to faults and defects that are not discovered during maintenance. For example, an investigation of a fighter aircraft crash by Ejaz et al. [84], discovered that the crash was due to the failure of the compressor rotor. A crack had initiated from machining marks on the disk then propagated along the machining mark causing fatigue.

A similar accident occurred due to fatigue in the central ball bearing of the compressor region that had been inspected five hours prior to the incident. The inspection showed that the "parameters measured was within the specified limits" [85].

The aerospace industry has had very noticeable improvements throughout the past decade. As seen earlier, inspection is not enough to label an aircraft safe to takeoff. CPS systems are now being implemented to provide pilots with real-time aircraft data monitoring. For example, Takeda et al. [86] proposed fiber Bragg grating (FBG) sensors for the long- term health monitoring of large-scale composite wing structures. By using FBG sensors, "the barely visible impact damages could be detected because the shape of the spectrum is severely distorted by the strain change due to the occurrence of damages". Applying CPSs not only on aircrafts but on any fatigue exposed structure could substantially decrease the risk of structural failure and allow real-time data to be presented to service centers. This means that aircrafts could be taken to maintenance centers whenever CPSs assess that it is required. As a result, this could prevent many accidents such as those mentioned earlier. Also, different methods combining CPSs and AI for product inspection has been proposed such as using convolutional neural network (CNN) for inspecting method for defective casting products [87].

2.5.3.4. Smart factories

Manufacturing is one of the highest energy consuming stages throughout the CE model. Currently, manufacturers are strongly leaning towards the adoption of energy saving strategies [88, 89, 90, 91]. One way of approaching a low power consumption manufacturing model can be through CPSs. For example, a proposed CPS based on multi-agent system (CPMAS) technology produced an intelligent demand-side management system that was able to reduce power consumption by 35% in the month of July in a building of approximately 2800 m^2. The proposed system relies intensively on the feedback loop of the CPS. The proposed system is composed of four different areas each with a specific task. These areas are the user area, the interface area, the analysis area, and the knowledge area. In general, sensors in the user area monitor the rooms and send data to the corresponding room agent in the interface area. This acts as an interface between the room and the system by producing detailed data of the user's habits. The data is then sent to the interface area where it is evaluated for the extraction of additional information. A proposed solution is then presented by each agent accordingly. If a critical condition is detected, it will be sent to the analysis area for the coach agent to evaluate proposed solutions and choose the most suitable one, which is sent back to the interface area. Lastly, the knowledge area stores the data related to power consumption, which includes solutions as well as the user's preferences from both areas, to deduce additional information [92]. Such systems can be implemented in manufacturing facilities on a larger scale that takes into consideration all the power equipment used in manufacturing as well as power consumption habits, such as cooling, heating, and lighting. Depending on the need, different sensors are placed in the user area, which contains rooms or sections in the manufacturing facility. The main task of the sensors is to obtain data from each room or section, such as recording temperatures throughout the day, measuring the light intensity and recording the user's preferences at different times. As mentioned earlier, the collected data is then sent to the corresponding room agent in the interface area that acts as an interface between the room and the system by producing detailed data of the workers' habits such as the preferred temperature, the light intensity, and the working times. The obtained data is then sent to the interface area where it is evaluated for the extraction of additional information, such as the number of people available at a specific time of the day.

Moreover, CPS manufacturing architecture could provide self-predicting and self-aware machine health monitoring systems. This architecture acquires data needed to generate meaningful information and provide a decision-making process for the end user [64]. Hence, machine health monitoring data can be obtained directly from machines. These data are processed, and a proposed solution is then presented by each agent accordingly. For example, when the number of people in the room changes, the solution is to increase or decrease the cooling or heating depending on the season; when no people are in the room, the electricity is turned off, and so on. In the case of a critical condition being detected, such as a sudden breakdown of a machine, information is sent to the analysis area for the coach agent to evaluate proposed solutions. The coach agent chooses the most suitable solution and sends it back to the interface area, which acts accordingly by either solving the problem if it is solvable or involving a human factor by automatically emailing or messaging the designated engineers or supervisors on duty and notifying them about the critical case. Overall, this could substantially reduce the amount of energy by omitting the human factor from controlling the power consumption and relying on the smart CPS to optimize the use of energy without affecting the comfort of the employees. Moreover, machine health monitoring allows for early machine diagnoses that provide time for the manufacturers to find solutions and avoid delays that could be caused if the machines were to suddenly stop working due to undetected problems. Figure 9 presents a general model that is based on [92] using a schematic of the proposed agency with an emphasize on other CPS components, such as self-aware, self-predicting sensors, actuators, as well as a feedback loop [64].

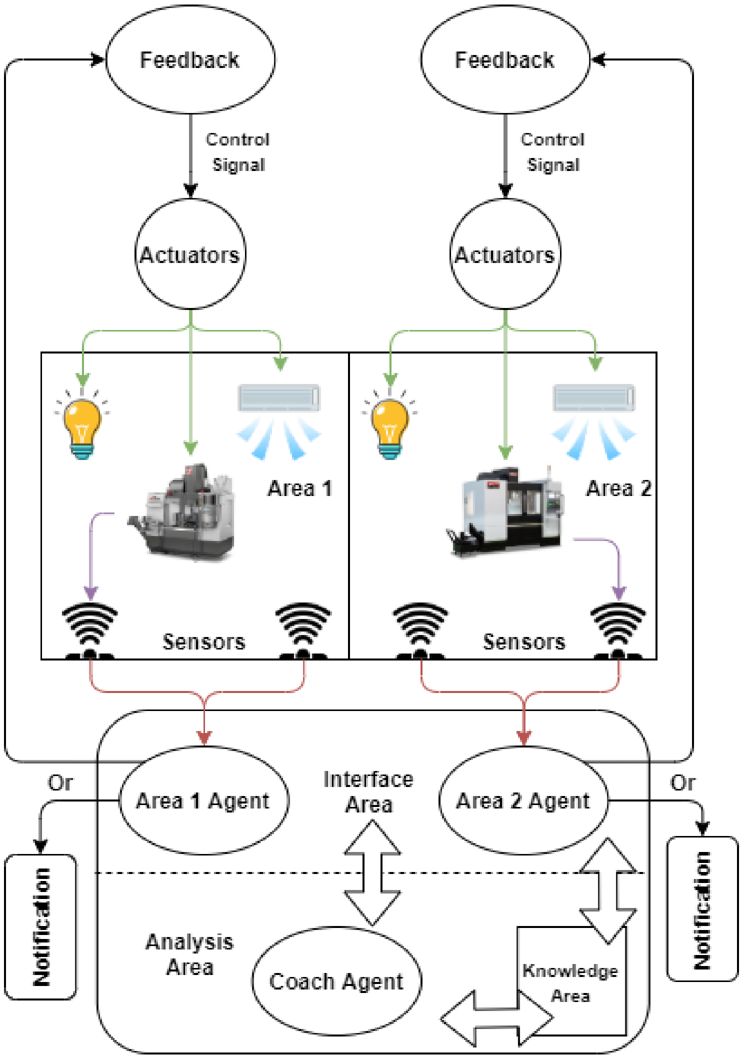

Figure 9: Proposed CPS of a manufacturing facility based on the model proposed in [92]

2.5.3.5. *Smart manufacturing performance measurement*

Smart manufacturing requires smart systems. CPSs are considered smart systems that integrate smart software applications with information and communication technologies that simultaneously optimize different performance metrics to deliver on-time, customized, high-quality products. In order to test and quantify the "smartness" of a manufacturing facility, specific performance metrics should be measured. Such performance criteria are productivity, quality, agility, and sustainability [93]. Most of these performance metrics can be easily collected and recorded using different types of sensors that can routinely collect all kinds of operational level data. This enables factories to have a real-time assessment of their production systems. Moreover, it is now possible to quantify the sustainability of manufacturing processes using CPSs that obtain the different measurements indicated by the "Standard Guide for the Definition, Selection, and Composition of Key Performance Indicators to Evaluate Environmental Aspects of Manufacturing Processes". Integrated CPSs then interpret the data and prepare a detailed report that includes all the parameters as well as efficiency scores of different manufacturing processes, for manufacturers to act upon, so they can increase their sustainability score.

2.5.3.6. Human-robot collaboration

Many manufacturing tasks require the collaboration of humans and robots. This has been increasingly implemented in many assembly lines. Sometimes human brains are needed to perform some tasks. However, humans lack precision. To have both human brains and precision at the same time, CPSs could be the best solution manufacturers could use. For example, a symbiotic human–robot collaboration is another implementation of CPSs in manufacturing. In this situation human-robot interactions and collaborations are made possible in areas such as dynamic task planning. Robots can be instructed by humans using gestures, signs, or speech during tasks such as collaborative assembly. As a result, resource efficiency and productivity are enhanced [57, 69].

2.5.3.7. Autonomous mobile material handling vehicles

Moving parts and materials to their assigned assembly station in a safe and timely manner is one of the challenging logistical problems for most assembly lines and systems. Mass customization has made that task even more challenging since the right part should be delivered to the right assembly line at the right time. This task would require a huge labor force as well as sophisticated scheduling that is very hard to achieve manually [94]. CPSs provide a solution in the form of autonomous mobile material handling vehicles that are widely referred to as "Automatic Guided Vehicles" (AVGs). These autonomous vehicles are being implemented and are almost a standard device in most assembly lines. Generally, automating material logistics and scheduling in an assembly line ensures safe material handling, a fast response to customized orders, and achieves zero errors if correctly operated. There are many types of AVGs in the market today and each type carries out different tasks in a manufacturing facility. For example, there are automated lift trucks, platform AVGs, heavy load AVGs and AVGs for the automation of assembly lines. Similarly, autonomous vehicles are being widely used in warehouses for product distribution.

Some other applications of CPSs in manufacturing are cyber-physical modules for machine tools, plug-and-work applications, automated generation of process plans, scheduling with alternative routings in CNC workshops, adaptive scheduling through product-specific emergence data, cyber-physical support for maintenance strategies, and cross-company information exchange for an adaptive production control based on early warning information [76]. It can be noted that the number of applications of CPS in manufacturing is unlimited. This is mainly due to the flexibility of these systems.

2.5.4 Distribution

As mentioned earlier, distribution is an essential stage in any economy whether it is linear or circular. Suppliers must distribute their products in a timely manner without any delays. Many distributers already use different CPSs, such as on-time tracking systems. However, there is room for more. Most difficulties faced by distributers involve complex distribution and transportation networks, such as prior planning for drivers, and heavy traffic that can cause delays. These factors have a great impact on the environment and product distribution management.

2.5.4.1. Using unmanned aerial vehicles in distribution

To solve traffic jams for short distance deliveries, unmanned aerial vehicles (UAVs), more commonly called "drones," are a typical CPS [95] that can be used over short distances for low weight distributions. Using drones in deliveries eliminates many of the negative impacts a normal delivery would have on the environment. UAVs operating with clean energy, such as solar energy, would reduce carbon dioxide emissions caused by conventional means of delivery as well as save substantial time during peak hours [96]. The main problem associated with drone delivery systems is due to the limited payload. The payload is the load that the drone can lift. Usually, drones with a higher payload are bigger and more costly and their risk of falling or failing suddenly makes them unreliable for deliveries. Currently, Amazon aims to implement drone deliveries for packages that weigh 5 pounds (2.268 kg) or less, with an estimated delivery time of 30 minutes [97]. The technology is still in the research phase and has many constraints, such as regulations, safety, and most notably, the design of the drone itself. However, research in this field is evolving quickly with encouraging results that indicate that this promising technology might revolutionize logistics.

2.5.4.2. Data communication virtual platform

Other challenges faced by suppliers and distributers are the complex production and transportation networks and the occurrence of disturbances. To overcome these problems, Farzzon et al. [98] presented a CPS improved supply chain model. The model highlights the use of CPSs in "data's communication virtual platform" which aims to represent a common world for suppliers, manufacturers, and distribution centers, permitting them to access different data regarding supply and demand as well as the available stock. In the proposed model the data flow between different stages of the distribution stage is facilitated by CPSs by providing a common data center.

2.5.4.3. Path decision ant colony algorithm

Another way of implementing CPSs in logistics is through the use of a CPS-oriented intelligent logistics path decision system [99]. The proposed system uses an algorithm called an "ant colony algorithm" (ACA). The system is derived from the behavior of ants foraging. Basically, ACA mimics how ants work using distribution centers as an ant nest where each ant is a distribution vehicle and the food for the ants serves as a distribution node. Ants determine the next distribution node based on the concentration of pheromones and the visibility of the path: the higher the visibility and the concentration of the pheromones, the shorter and more optimal the path is. Based on this, P indicates the probability of the next node being selected. A larger P indicates a greater possibility of being selected and a greater possibility of forming an optimal path. It should be noted that the virtual pheromones used in the algorithm have the same volatility as the pheromones released by ants. If a specific path is not being selected often, the pheromones will slowly evaporate leaving very low concentrations. This indicates that the path needs to be eliminated since it is not accessed often. In contrast, there will be more pheromones on a frequently accessed path, which indicates that this path is more convenient and more likely to become a distribution node. Similarly, ACA bases its selection of the optimal distribution path through different positive feedbacks.

The collected positive feedbacks provide an iteration of the optimal. In the end, the optimal path is chosen by finding the optimal solution for the optimal choice of the logistics distribution path [99]. Through the use of such an algorithm, distributers could easily overcome the complexity of transportation routes saving substantial time, cutting down costs, and reducing greenhouse gas emissions.

2.5.5 Usage

Similar to manufacturing, consumers experience a handful of CPSs throughout their daily lives. The main purpose of using CPSs on the consumer level is to enhance their experiences with products by omitting simple but time-consuming tasks. Not only that, but CPS could also aid people with extensive spinal injuries by helping them to easily interact and merge with today's world of fast-growing technologies. Furthermore, CPSs provide a new means of health monitoring strategies in the form of portable devices. CPSs also help connect the usage stage to the rest of the CE stages, since most of the time the CE cycle ends at this stage due to the very limited interaction between consumers and other CE stages.

2.5.5.1. Neuralink

People with extensive spinal injuries face many difficulties when interacting with today's technologies. Most of the time, simple tasks such as typing are considered difficult if not impossible. However, to make this possible, a bridge is needed to connect people with their devices without having them use their hands. For example, a person would be able to type without using the keyboard, would move the cursor without moving or touching the mouse, or even drive a car by just thinking about it. CPS has changed this from science fiction to reality. This can now be done using EEG-based non-invasive brain interfaces using neural implanting that would allow people to do various tasks by just thinking about them [52]. Announced by Facebook, the "typing-by-brain" project promises to enable people to type a 100 words per minute [100], in contrast to the record of eight words per minute accomplished by Stanford University using a brain-computer interface [101]. Another initiative is the "Neuralink," which has an initial goal of helping people with extensive spinal injuries regain control of computers and mobile devises. In doing so, it Is hoped that various neurological disorders can be treated, and people will be able to communicate easily through text or speech synthesis, while sensory and movement function is restored and new ways of interactions both between humans and between humans and technology are created. This is accomplished through micron-scale threads that are inserted into areas of the brain that control movement. Each thread contains many electrodes and connects them to an implant called the Link, which is a sealed device that processes, stimulates, and transmits neural signals [102]. The potential implementations of such CPSs are enormous. For example, people could drive cars using their brains, which would significantly reduce the driver's reaction time since the car would respond directly to the driver's thoughts. When the technology is ready, it could be easily implemented in electric cars. Moreover, simple tasks such as recording an event on a calendar, controlling the TV, lights, heating, cooling etc. would be just a thought away.

2.5.5.2. Portable health monitoring devices

Nowadays, sensors can be embedded into very small devices such as watches. Watches with sensors and computing capabilities are labeled as smart watches. Through these watches, a person can obtain a continuous reading of their sweat glucose [103] and measurements of physiological parameters, such as heart rate, galvanic skin resistance, and temperature [104]. As well they can monitor health in home-based dementia care [105], monitor respiratory rate and body position during sleep [106], monitor symptoms in advanced illness [107], and even detect the early symptoms of COVID-19 [108]. The capabilities of these devices are endless and are only constrained by innovations in the electromechanical field.

2.5.5.3. Adaptable electronics

Smart electronics, such as televisions, smart phones, smart fridges, and smart homes, can easily adapt to the person using them. Motion sensors and accelerometers in smart phones detect and record movements throughout the day. This data is interpreted and is used to customize user experiences. For example, a smart phone is capable of understanding that you are having lunch by obtaining your location, the time of day, and your usual activities during the same time on previous days. Your phone could then send you a notification reminding you that it is lunch time and could even suggest a restaurant. The same applies to smart televisions that suggest movies based on previous activity and recorded preferences. Machine learning facilitated by CPSs provides a new means of people-machine interactions in the effort to create a smoother and friendly user experience.

2.5.6 Recycling

To maintain the circular nature of the economy, recycling should be optimized to return as much material as possible into the economy and reduce outputs to landfills. There have been many proposed waste collection processes that implement CPSs. Different papers have proposed CPS-based smart waste collection systems that integrate cyber and physical spaces to compute, control and communicate all components of waste management, while others have proposed CPS-based recovery methods for waste electrical and electronic equipment (WEEE) [109] [110]. Initially, a "digital twin" method was proposed by NASA [109]. Simply stated, "It indicates the simulation of an (aerospace) vehicle or system that uses the best available physical models, sensor updates, fleet history, etc." The main point of using a digital twin in WEEE management is to merge data from the physical world and the software system in the cyber world. However, the proposed idea requires an interactive collaboration between all stages of the CE with almost all Industry 4.0 enablers working simultaneously to serve its purpose. Hence this topic will be discussed further in the inter-impact section of this paper. Another approach aims to deploy CPS components, such as sensors and actuators, to improve the end-of-life processing of electrical and electronic equipment (EEE) [110]. This approach mainly relies on sensors, such as radio frequency identification tags (RFID), to allow the monitoring of waste throughout the waste management process.

2.5.6.1. Radio frequency identification (RFID) waste sorting system

A full automation of the recycling process would require very smart and adaptive technologies. Waste sorting is a critical part in recycling. Each type of material needs to be treated differently. Aluminum cans are melted at very high temperatures, while doing the same to plastics poses high environmental and health risks due to the poisonous fumes that are emitted. Hence, it is critical to sort materials before applying any specific treatments. For that reason, radio frequency identification can be used. RFID is a tag that is very flexible and can vary in size and shape. These tags can store data that can be read when scanned by an RFID reader. RFID readers can be attached to sorting machines, which can then read the data from each object to identify its material, thus making it easier for the machine to sort. For example, aluminum cans can be easily identified. WEEE can also be easily identified. Organic materials will not usually have these chips so it can be sent directly to farmers to use as fertilizers. Moreover, this also ensures that medical waste is treated separately and with extra care and that industrial materials are returned to manufacturers for remanufacturing and reuse. There are available waste sorting techniques and machines; however, these machines are not efficient when exposed to mixed waste and only work with bulk. Hence, CPSs would provide an easily implemented and efficient solution for waste sorting and management.

2.6. Sustainable Development Goals

Sustainable development goals (SDGs) are 17 interlinked goals set by the United Nations in 2015 and are designed to "promote prosperity while protecting the planet. They recognize that ending poverty must go hand-in-hand with strategies that build economic growth and address a range of social needs including education, health, social protection, and job opportunities, while tackling climate change and environmental protection" [111]. Summarized in Table 2, this section presents how each technology discussed earlier within each CE stage contributes to different SDG.

2.6.1 Sourcing

The automation of mining in the sourcing stage directly achieves the third goal as its main goal is to ensure a safe working environment by eliminating risk factors in the mining process. The implementation of CPSs in the sourcing stage also contributes to the eighth goal as it eradicates forced labor, slavery, and human trafficking by eliminating the human factor in the mining process. As a result, it promotes decent work and economic growth. It also directly achieves the ninth goal of industry: innovation and infrastructure. An important advantage for automation of the mining stage is a significant reduction in inequality, mainly in the form of gender inequality, as the physical factor, in which males usually dominate, is eliminated since the mining processes are controlled through computers. Hence, automation of the mining stage has a direct impact on fifth SDG goal as well.

2.6.2 Design

The design stage targets several SDGs as it determines how the product will be manufactured, used, and disposed. Firstly, the design information feedback system achieves the ninth goal of Industry, innovation and infrastructure, and the twelfth goal of reasonable consumption and production since data and knowledge is used to verify the final design of the products before approval; thus, fewer malfunctioning products are manufactured. Energy savings, cost reductions, and an increase in the lifetime of the products and goods are achieved. As a result, it indirectly contributes to attaining a sustainable environment, which is the eleventh SDG. Similarly, testing and simulation assistance in product designs achieve the same goals. The use of simulations reduces emissions caused by actual testing of sophisticated products such as planes or cars. Most of the time, individual parts can be tested in a controlled environment without the need of real-time operation. This directly contributes to the thirteenth goal of climate action. Design for manufacturing and assembly also targets the 9^{th}, 11^{th} 12^{th} and 13^{th} goals for similar reasons. In addition, through the elimination of many unnecessary materials and manufacturing processes, the stress on the environment is reduced, thus indirectly contributing to the 14^{th} and 15^{th} goals of life below water and life on land, respectively. Moreover, it provides the easiest, cheapest, and most efficient route for product manufacturing and assembly contributing directly to the decent work and economic growth. Overall, the design stage in a CE can achieve at least seven of the SDGs.

2.6.3 Manufacturing

The manufacturing stage contributes to the most goals among the CE stages. it is safe to say that all the CPS technologies in this stage achieve the ninth goal. It can be observed that the implementation of CPSs in this stage contributes either directly or indirectly to the good health and well-being of employees and customers, thus achieving the third goal. Similar to automation in the sourcing stage, manufacturing process automation also contributes to the fifth and tenth goals of gender equality and reduced inequalities, respectively. Moreover, since smart factories and smart performance measurements serve the same purpose, both achieve the same SDGs which are the 3^{rd}, 7^{th}, 9^{th}, 11^{th}, 12^{th}, and 13^{th} goals, while indirectly contributing to the 14^{th} and the 15^{th} goals. This is mainly due to the intense reliance of smart factories on clean energy for operations. As well, this can be integrated into smart and sustainable cities, with reasonable on-demand production that include highly efficient and clean production systems. This reduces greenhouse gas emissions and subsequently, the stress on life both on land and below the water. Overall, applying CPSs in manufacturing in a CE can achieve at least ten of the SDGs.

2.6.4 Distribution

Similar to the manufacturing stage, the ninth SDG can also be considered a common achievable goal among the implementation of different CPSs in the distribution stage. Moreover, the use of UAVs eliminates inequalities as its operation can be done using controllers or built-in algorithms, which can be handled by people with disabilities. If UAVs use electricity generated from clean energy, they will directly achieve goals 14, 15 and 16. To continue, the path decision of the ant colony algorithm chooses the most convenient, safest and shortest paths for drivers to follow, thus achieving the 3rd, 13th, 14th, and 15th SDGs. In addition to the ninth SDG, the data communication virtual platform achieves the eleventh goal through enabling a common data sharing platform that allows multiple vendors and distributors to manage inventories in a sustainable manner.

2.6.5 Usage

Several CPSs can be deployed to achieve certain SDGs at the usage stage. For example, Neuralink and different portable health monitoring devices directly contribute to the third SDG of good health and wellbeing. Neuralink and adaptable electronics can also contribute to the fourth SDG if utilized in education by either helping people with severe spinal injuries with their education or personalizing education based on a pupil’s needs and interests. With regards to the product, however, the user determines if it will achieve different SDGs by how it is used and disposed of. This is unlike the service point of view discussed earlier, in which the technology determines the goals to be achieved.

2.6.6 Recycling

The projected recycling stage would serve its purpose by returning the materials into the CE. The use of RFID tags could significantly enhance and increase the efficiency of the recycling process, which would directly contribute to the enhancement of the circular economy and achieve the eleventh SDG: sustainable cities and communities. Recycling also contributes to the thirteenth SDG (climate action) by reducing mining and different manufacturing processes needed to make new products. Eventually, greenhouse gas emissions would be lowered and waste disposal in the seas decreased, protecting the lives of different species under the sea and on land as targeted in the fourteenth and fifteenth SDGs.

Table 2: SDGs achieved by the implementation of different CPSs along with each of the CE stages ((**x**) - Directly achieved (**0**) - Indirectly achieved).

		Sustainable Development Goals (SDGs)																
Circular Economy Stage	**Implementation**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
Sourcing	Autonomous mining operations	-	-	x	-	x	-	-	x	x	x	-	-	-	-	-	-	-
Designing	Design information feedback system	-	-	-	-	-	-	-	-	x	-	0	x	-	-	-	-	-
	Testing and simulation assistance in product design	-	-	-	-	-	-	-	-	x	-	0	x	x	-	-	-	-
	Design for manufacturing and assembly	-	-	-	-	-	-	-	x	x	-	x	x	x	0	0	-	-
Manufacturing	Quality control and quality assurance	-	-	x	-	-	0	-	-	x	-	x	x	-	-	-	-	-
	Machine tools health monitoring	-	-	0	-	-	-	-	-	x	-	-	x	-	-	-	-	-
	Products health monitoring	-	-	0	-	-	-	-	-	x	-	-	x	-	-	-	-	-
	Smart factories	-	-	x	-	-	-	x	-	x	-	x	x	x	0	0	-	-
	Smart manufacturing performance measurement	-	-	x	-	-	-	x	-	x	-	x	x	x	0	0	-	-
	Human-robot collaboration	-	-	x	-	x	-	-	-	x	x	-	-	-	-	-	-	-
	Autonomous mobile material handling vehicles	-	-	x	-	-	-	-	-	x	-	-	-	-	-	-	-	-
Distribution	Using unmanned aerial vehicle in distribution	-	-	-	-	x	-	-	-	x	x	x	-	x	x	x	-	-
	Data communication virtual platform	-	-	-	-	-	-	-	-	x	-	x	-	-	-	-	-	-
	Path decision ant colony algorithm	-	-	x	-	-	-	-	-	x	-	-	-	x	0	0	-	-
Usage	NeuraLink	-	-	x	x	-	-	-	-	x	-	-	-	-	-	-	-	-
	Health monitoring portable devices	-	-	x	-	-	-	-	-	x	-	-	-	-	-	-	-	-
	Adaptable electronics	-	-	0	x	-	-	-	-	x	-	x	-	-	-	-	-	-
Recycling	Radio frequency identification (RFID) waste sorting system	-	-	-	-	-	-	-	-	x	-	x	-	x	x	x	-	-

2.7. CE Assessment Tool

The adoption of an I4.0 enabled CE has been proven to be an effective solution in tackling many of modern-day accumulated complications caused by industrialization and human activities since the first industrial revolution in the 17th century.

Many developed countries have shifted from the linear conventional economy model to a CE model. With its economic, social, and environmental benefits, many developing nations are to follow. With such foundations, nations could easily improve their wealth, prosperity, and abundance. However, to what extent can the implementation of these tools contribute to the CE?

As reviewed earlier, I4.0 effectively contribute to the circularity of the economy [112]. Many other procedures, standards, and factors also play an important role in determining the circularity of the economy. However, depending on each individual case, some factors may impact the circularity more than other. As stressed by the economist Peter Drucker, improvement, or manageability of a system, implies the measurability of that system [113]. In order to be able to capture the progress made towards circularity, an assessment tool should be established. For it to be effective, it should be able to measure the effectiveness of the CE of a wide range of sectors. So far, there are no common accepted procedures to measure CE performance [114].

Literature shows that deep research on CE assessment tools and indicators is still lacking [115]. Also, there is a need to establish a set of indicators to monitor the transition to CE [116]. Very few CE indicators frameworks are available, most of them fail to capture some important dimensions such as policy implementation towards CE [117]. Literature lacks a comprehensive scaling/rating system that accounts for all CE dimensions including non-manufacturing ones such as customers' contributions, policies, regulations, and technological advancements.

An effort was made by Sassanelli et al. [118] to highlight different assessment tools in a systematic literature review that showed some potential in this field. However, none of the presented assessment procedures are comprehensive, many fail to capture all the dimensions of the CE at once, and many others are subjective. To illustrate, there are several tools intended to assess the CE performance on different scales. A well-known tool is Circulytics® by the Ellen Macarthur Foundation [119]. The tool measures the

CE performance of company's material and water flow and other services provided along with energy use. This tool however is a company-level (micro-level) measuring tool and cannot be implemented on other CE levels such as the macro and meso levels. Also, the tool requires direct input from users, which adds an undesirable level of subjectivity to the results.

Another assessment tool is the Cradle to Cradle Certified® by the Cradle-to-Cradle Products Innovation Institute [120]. Similarly, the tool is used to assess products made for the CE (micro level) and cannot be used on the macro or meso levels. Moreover, the tool lacks flexibility even on the product level as it does not assess products that consumes nuclear energy or uses non-renewable resources. Another tool proposed by Chun-rong & Jun, 2011., assesses regional CE based on matter element analysis [121]. Like the previous tools, it only assesses CE on a meso scale and uses a basic grading system. IFIXIT is another tool that assesses the repairability of mobile devices, which directly contributes to the recycling stage of the CE, based on a specified criterion. This score however cannot be used individually to assess circulatory of mobile devices but gives valuable insights on whether the device can fit into a CE or not. Table 3 presents the previously discussed assessment tools along with their limitations.

2.8. Summary

This chapter highlighted the need of an assessment tool that measures the circulatory on different scales of the economy (micro, meso and macro). It can be concluded that the area of CE assessment tools lack the following: 1) A comprehensive I4.0 tools guide to facilitate and ease their implementation along the CE; 2) A universal tool to assess the readiness of a facility or a country to adopt a CE model and grade it based on the efficiency of adoption, the overall products quality of the products, and the potential improvements, and 3) A set of measures and standards to qualify SDG achievements and act as a guideline for different operations. This will be achieved through the development of a comprehensive multi-level CE assessment framework in the next chapter of this thesis.

Table 3: CE assessment tools available and their limitations

Source	**Assessment tool**	**Limitations**
Ellen MacArthur Foundation [119]	Circulytics®	- Not a comprehensive tool, compatible for measuring companies CE performances only (Micro-Level)
Cradle to Cradle Products Innovation Institute [120]	Cradle to Cradle Certified®	- Not a comprehensive tool, compatible for measuring products CE performances only (Micro-Level) - Does not assess products that consumes nuclear energy or uses non-renewable resources
(Chun-rong & Jun, 2011) [121]	Evaluation of Regional Circular Economy Based on Matter Element Analysis	- Not a comprehensive tool, compatible for measuring CE performances regionally only - Basic grading system
IFIXIT [122]	IFIXIT	- Measures mobile devices circulatory only (Micro-Level) - Cannot be used alone to assess the circulatory of the devices.

Chapter 3. A Multi-Level Circular Economy Assessment Framework for the Private and Public Sectors

The aim of this chapter is to present a comprehensive CE assessment framework that is capable of assessing the circularity of 1) developed and developing countries, 2) different industries, 3) wide range of processes and 4) different products, of both private and public sectors on a micro, meso, and macro levels. This is achieved through a step-by-step indicators selection procedure and the combination of fuzzy logic and multi-criteria decision-making (MCDM) methods which deliver a superior methodology in CE assessment that can easily eliminate previously mentioned problems and result in a realistic and an unbiased ranking of alternatives.

3.1. Introduction

Many factors such as global warming, environmental pollution, and resources scarcity caused a fast based trend in the transition from linear to circular economies. However, to adequately achieve the intended economic, environmental, and social goals of the CE, the development of an assessment tool and a monitoring structure are critical to ease progresses measurability towards circularity [123]. So far, there are no common accepted procedures to measure CE performance [114]. Literature shows that advanced research on CE assessment tools and indicators is lacking [115]. Also, there is a need to establish a set of indicators to monitor the transition to CE [116]. Very few CE indicators-based frameworks are available, most of them were unable to capture some important dimensions such as policy implementation towards CE [117]. Literature lacks a comprehensive scaling/rating system that accounts for all CE dimensions including non-manufacturing ones such as customers' contributions, policies, regulations, and technological advancements. An effort was made by Sassanelli et al. [118] to highlight different assessment tools in a systematic literature review that showed some potential in this field. However, none of the presented assessment procedures captures all the dimensions of the CE at once. To illustrate, there are several tools intended to assess the CE performance on different scales. A well-known tool is Circulytics® by the Ellen Macarthur Foundation [119]. The tool measures the CE performance of company's material and water flow and other services provided along with energy use. This tool however is a company-level (Micro-level) measuring tool and cannot be implemented on other CE levels such as the macro and meso levels. Also, the tool requires direct input from users, which adds an undesirable level of subjectivity to the results. Another assessment tool is the Cradle to Cradle Certified® by the Cradle-to-Cradle Products Innovation Institute [120]. Similarly, the tool is used to assess products made for the CE (Micro level) and cannot be used on the macro or meso levels. Moreover, the tool lacks flexibility even on the product level as it does not assess products that consumes nuclear energy or uses non-renewable resources. Hence, a comprehensive CE measuring or rating system is needed to allow companies, firms, sectors, and countries improve their circulatory on a micro, miso, or a macro scale, as well as provide standardize data collection and information management sharing systems that would ease the collaborations between different firms along the CE cycle and allow for an easy, comprehensive and a standardized assessment procedure.

As highlighted earlier, a predefined standard set of indicators for either a macro, meso or a micro level CE is very challenging to be achieved. This is mainly due the unlimited variety of scopes, goals, characteristics, and challenges different countries, firms, enterprises, and products have. However, the proposed framework addresses this gap by providing the user with a step-by-step procedure that accounts for different dimensions that any country, industry, or product may require whether it is applied to a private or public firms, to guide the user with choosing and using a tailored set of indicators that correctly assess the CE performance of the assessed body. Unlike other frameworks presented earlier, the proposed framework provides flexibility in indicators selection while eliminating subjectivity and randomness through the predefined constrains that lies within the scope of each defined level. Moreover, it incorporates fuzzy logic and rule based expert systems to facilitate the merging between related indicators which provide users with realistic scores and drastically decrease uncertainties that lies within linguistic terms and values obtained from the indicators. Finally, the proposed framework uses a combination of different multi-criteria decision making (MCDM) methods to obtain the final score and accordingly, selects the best alternative. The framework presented is intended to add on to the available sustainability frameworks used in the industry by providing a complementary assessment procedure that measures the CE performances of different processes and products on a wide scale for different industries from developed or developing countries and on both private and public sectors.

3.2. Framework Development

As mentioned earlier, the main aim of this paper is to develop a comprehensive CE assessment framework that is characterized by its flexibility, ease of use, as well as accuracy in determining the most suitable alternative among processes or products that best follows the conventional five-stages CE model. As presented in Figure 10, the framework is composed of four stages. In the first stage, users are required to collect four sets of indicators. These indicators should be able to distinctly define the level of the product or process based on a three levels scale: macro, meso and micro as explained in section 3.4.1. The next set of indicators are directly related to the industry the assessed product or process is involved in as presented in section 3.4.2. Afterwards, indicators that directly emphasize on CE model practices and stages are defined. These indicators can be obtained from literature, organizations, experts or previously used life-cycle-assessment and other similar approaches as it will be highlighted in section 3.4.3. Lastly, different sustainable development goals achieved by the process, or the product are listed. Depending on the relative importance of the goal to the assessed field, scores are assigned on a scale of [0,1].

In the second stage, fuzzy logic is implemented on the different indicators collected earlier to automate the process of converting qualitative and quantitative indicators to scores. Moreover, fuzzy logic gives users flexibility in their choices of indicators with the help of membership functions. Most importantly, the rule-based expert system implemented in the fuzzy inference system (FIS) allows the merger of many related indicators into one score as presented in section 3.5.

Assigning weight of indicators takes place in the third stage where either subjective or objective weight assignment methods are used. If subjectivity is to be avoided, the entropy method is used to determine the weights. On the other hand, when users require experts to assign the weights, then the analytical network process (ANP) is used. Lastly, different MCDM methods are used to normalize, assess, and aggregate the results and produce final scores for the different alternatives to be ranked based on their final circularity scores.

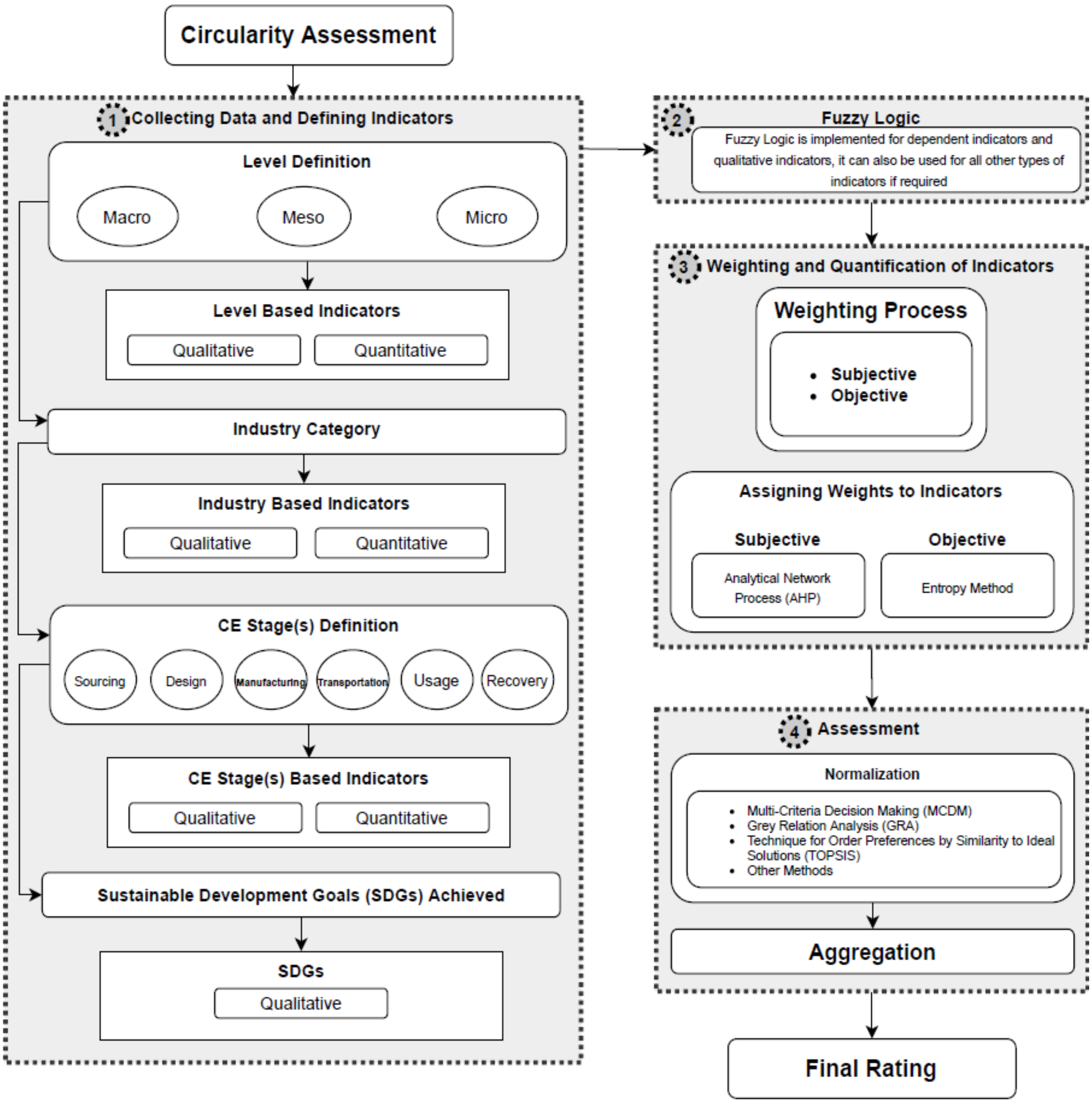

Figure 10: Circular Economy (CE) Assessment Framework

3.3. Choosing the Correct Indicators

After the required indicators are defined and selected, data obtained from each of the selected indicators are classified into two main groups, quantitative and qualitative. Qualitative indicators measure amounts and quantities in units. While qualitative indicators measure change over time against certain preset criteria [124]. For example, the amount of greenhouse gases emitted during a process is a quantitative indicator that is measured in cubic meter. Likely, the power consumption of a factory is also a quantitative indicator that is measured in kilowatts. On the other hand, qualitative indicators are a measure of people's perception about the measured parameter such as the quality of work, product's performance or improvements in research and development across a firm or within a country [125]. Unlike quantitative indicators, qualitative indicators cannot be directly measured using conventional measurements instruments as they do not necessary involve enumeration. Instead, measuring qualitative indicators require different collection strategies such as surveys, historical data, and experts' opinions. Indicators can be further broken down into other advanced groups. For example, qualitative indicators can be categorized into two sub-groups that are open-ended qualitative indicators, which are based on the respondents' opinions on the qualities of the project that they deem to be important, and focused qualitative indicators which focus on specific qualities of interest. Another type of indicators are the compound indicators. A compound indicator is one that has a standard in it that needs defining and assessing. For instance, finding the number of projects completed that meet a specific criterion is an example of compound indicators. Moreover, scale and indices indicators are ones that combine many indicators into one such as the human development index.

Lastly, proxy indicators are approximate indicators that are not precise such as the satisfaction level of people living in a certain area [125]. Figure 11 summarizes the different types of indicators that users of the proposed framework should consider to be able to obtain a comprehensive choice of indicators set.

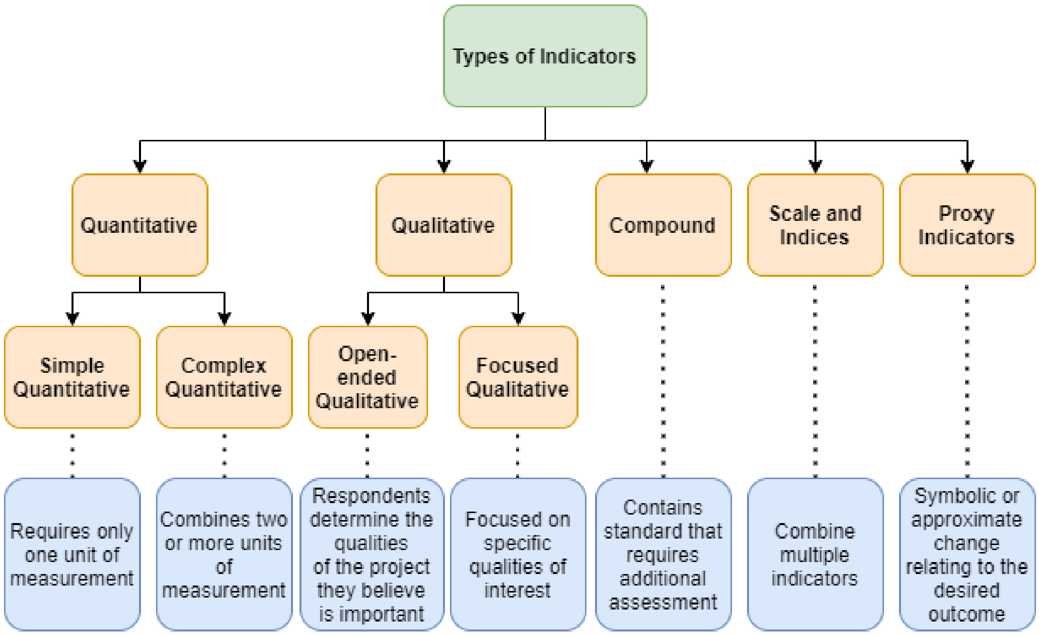

Figure 11: Types of indicators that are to be selected for the CE assessment, obtained from [126]

The indicators are then further filtered bases on a checklist to end up with clear indicators only. A set of indicators should follow the following criteria before being approved to be used [125]:

- **Targeted**: The set contains indicators that defines the 4 four "Ws" that are:

  1. What is Changing? (Element of Change)

  2. Who is involved in changing? (Targeted group)

  3. Where is the action or change happening? (Location or level)

  4- When is the change happening? (Timeframe)

- **Measurable:** All indicators should be easily measurable and have the following:

  1. Specific units of measurement

  2. Allow comparison

  3. Qualitative indicators should have defined qualities using words like "successful, appropriate, effective."

- **Reliable**

  1. Information used are from credible sources

  2. Minimum assumptions are used and are clearly stated

  3. Slight to no variation in information collected by different people for the same purpose

  4. Direct connection between the indicator and its collected information

- **Feasible**

  1. Indicator's information could be obtained

  2. Verification of the information is doable

- **Utility in decision-making**

  1. Indicators are linked to key factors

2. Indicators’ information have major impact on decisions

3.4. Collecting Data and Defining Indicators

3.4.1 Level definition

The first step in the assessment procedure is to determine the level of the economy of the assessed body. Based on that, a tailored level-based indicator set is selected for the assessment. As mentioned earlier, the CE can be graded over three different levels: micro level, meso level and macro level. Determining the level of the CE is very important as it supports the classification of the different available indicators. This eases the assessment procedure by eliminating unnecessary indicators. Also, it eases standardization efforts by designating a specific organizational body to select and set standard indicators for each specific level. The definition of each level slightly varies in literature. The following sections of the paper define a clear criterion distinguishing between each level, which allows users of the proposed framework to correctly define the level of the assessment and the designated indicators.

3.4.1.1. Micro level

Minor operations and final products should be taken into consideration to correctly assess CE performances. The micro-level scale considers specific processes at a company or a local level, it also considers individual substances and products [127]. The main aim of micro-level indicators is to describe the performance of a company or product from an environmental, economic, and social perspectives. Due to the small-scale micro level indicators are applied on, they can provide detailed analysis on specific material category or emission [127]. The assessment is carried out based on the micro-level indicators for the following categories of activities on a **company** scale:

- Consumption of resources (Primary & Secondary)
- Production of goods
- Processes
- Services
- Value added and jobs
- Corporate R&D

- Waste disposal
- Air emissions

As well as the following categories on a **product** scale:

- Products overall sustainability
- Products overall performance

3.4.1.2. Meso level

The meso level CE covers a range of practices applied within the economy. This covers different industries, branches of production and categories of consumption [128]. Indicators of the meso level focuses on detecting the activities of a specific consumption domain or sector [128]. For example, indicators detect the level of waste materials, efficiency of the production processes and the pollution caused by a specific sector. In other words, meso level indicators focuses on assessing the performance of plants or industrial parks. The assessment is carried out based on the meso level indicators for the following categories of activities in on an industrial park scale:

- Primary resources consumption (Raw Materials)
- Secondary resources consumption (Recycled Materials)
- Utilization of resources
- Waste disposal or treatment
- Air Emissions

3.4.1.3. Macro level

Most of the CE practices such as recycling, repairing, reuse, remanufacturing, and refurbishment take place within national boundaries. Nevertheless, the incorporation of CE within international trade is as significant as the practices mentioned earlier. The Macro level of the CE focuses on the exchange of sources (Materials) between the environment and the economy, and the exchange of products, on international trade [116]. In other definitions, the Macro level also addresses general CE activities of a nation [129]. Further details of the different economic activities withing the nation is addressed through the meso level CE as mentioned earlier. The assessment is carried out based on the macro level indicators when materials and goods fall under one or more of the following categories of **international trades**:

- Primary resources (Raw Materials)
- Secondary resources (Recycled Materials)
- Manufactured goods
- Used (Second hand or refurbished) goods
- Waste and scrap

As well as the following categories on a **national** scale for the overall:

- Extraction of resources
- Consumption of resources
- Utilization of resources
- Waste disposal or treatment
- Air emissions

Figure 12 presents the classification of the macro, meso, and micro levels across the economy.

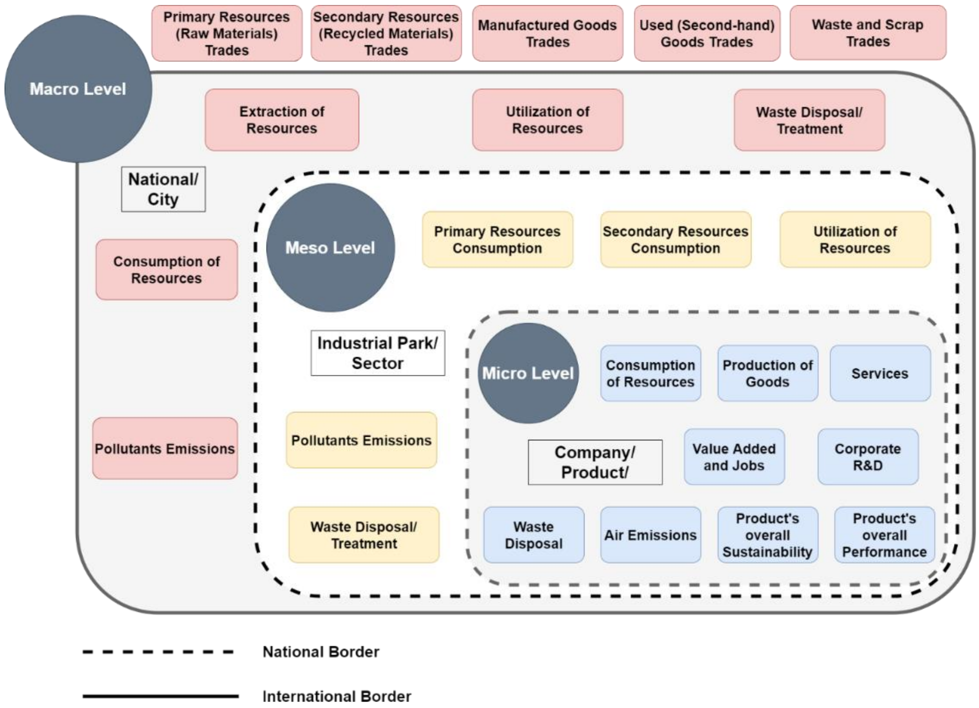

Figure 12: Macro, Meso and Micro Levels Classification

3.4.1.4. Level-based indicators

The user is then required to choose the correct set of indicators that should cover environmental, economic, and social aspects. If the assessed body is covered by one or more than one category, the user should select indicators that are related to these specific categories. Generally, indicators can be classified into five categories. The five different categories are: economic indicators, input indicators, output indicators, consumption indicators and, the capita figures indicators category [128]. However, the capita indicators category falls under the macro level only since this level consider cities and countries hence the capita set of indicators present a way of comparing regions and cities without being influenced by their sizes or demographics. The five different categories are presented in Figure 13.

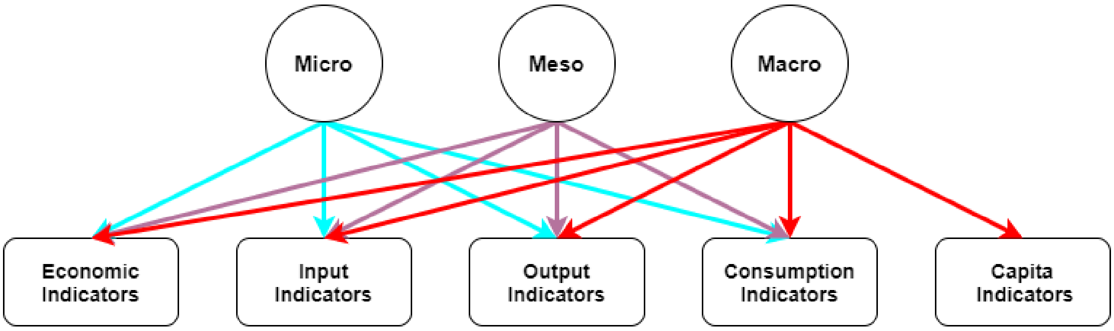

Figure 13: The five main categories of levels' Indicators

For each of the five categories, the user of this framework should include indicators that are classified as either environmental, economic, or social. Sometimes, indicators may fall under more than one category at once. The indicators falling under each of the five categories varies from one level to another. Table 4 presents examples of indicator sets for each level.

3.4.2 Industrial category indicators

The next set of indicators users of the proposed framework are encouraged to gather and utilize are the ones that directly represents the industrial category of the assessed object. To further assist users of the proposed CE assessment procedure, it is advised to use industry taxonomies based geographical location. For example, if the CE assessment is carried on in North America, the North American Industry Classification System (NAICS) is used to accurately classify the assessed object [135]. However, if the geographical location is not supported by any classification systems, then the United

Nations Standard Products and Services Codes (UNSPSC) is to be used [136]. Table 5 summarizes some of the most common industry taxonomies form some geographical locations.

Table 4: Different sources of Level indicators in literature

Level	Source	Number of Indicators / Built in Indicators (Assessment tool)
Micro	IFIXIT [130]	Built-in Indicators
	Saidan et al. [131]	20 Indicators
	Ellen MacArthur Foundation	36 Indicators
	Summa Circular Economy Policy Research Centre [128]	7 Indicators
	Cradle to Cradle Certified® [120]	Built-in Indicators
Meso	Geng et al. [132]	12 Indicators
	Saidan et al. [131]	16 Indicators
	Geng et al. [129]	38 Indicators
	Summa Circular Economy Policy Research Centre [128]	10 Indicators
Macro	Geng et al. [132]	22 Indicators
	CTI TOOL [133]	10 Indicators
	Summa Circular Economy Policy Research Centre [128]	9 Indicators
	Haas et al. [134]	13 Indicators
	Saidan et al. [131]	19 indicators

Table 5: Common industry taxonomies based on geographical locations

Location	Classification System
Australia & New Zealand	Australian and New Zealand Standard Industrial Classification (ANZSIC)
European Union	Statistical Classification of Economic Activities in the European Community (NACE)
United Kingdome	United Kingdom Standard Industrial Classification of Economic Activities (UKSIC)
Sweden	Swedish Standard Industrial Classification (SNI)
North America	North American Industry Classification System (NAICS)
Other	United Nations Standard Products and Services Code (UNSPSC)

After the industry is clearly defined, users collect indicators that fall under the defined industry. Several industry-tailored indicators are found in literature. For example, M.Elhuni and Ahmed proposed a set of key performance indicators (KPIs) for evaluating the sustainable production in the oil and gas sector [137]. Furthermore, D'Adamo et al. [138] proposed two versions of an indicator that measures the socio-economic performance of bioeconomy sectors. The first version considers all bio-based sectors, while the other focuses on manufacturing and bio-energy sectors. Similarly, other KPIs where identified in different other sectors such as for the healthcare facilities maintenance [139], automotive components' manufacturing organization [140], and for industrial supply chains [141].

3.4.3 Circular economy indicators

Circular economy (CE) is a waste conservative model that is defined as "*An Industrial system that is restorative or regenerative by intention and design*" [35]. CE aims on protecting the environment while achieving a prosperous economic development and taking into consideration social aspects [142, 143]. This is mainly achieved by focusing on recycling, re-use, repair and remanufacture. As well as by developing new systems and business models and changing consumption patterns [127].

Generally, for a product or a process to be regarded for a CE model they have to undergo five main and two interconnecting stages. The main five stages are: sourcing, manufacturing, distribution usage and recovery. The interconnecting stages are designing and transportation. In order to adequately conduct a CE assessment, there should by a clearly defined indicators that directly corresponds to the CE model.

For example, the integration of industry 4.0 tools such as cyber-physical-systems, cloud computing and internet of things, is an important factor in determining the compatibility of the assessed product or process to the CE model.

Other CE indicators may be directly related to the connection between different stages of the CE. For example, the manufacturing and recycling facilities represent two different stages in the CE model. Both stages are strongly encouraged to be connected to facilitate a smooth on-demand flow of recycled materials from the recycling to the manufacturing facilities. CE indicators can be unlimited; hence, it is suggested that can be obtained either from literature or from experts in the field. For example, several indicators are presented to measure the performance of a product with respect to CE principals [144].

Moreover, the Ellen MacArthur Foundation presented different indicators that focuses on measuring material circularity [119]. Also, other indicators that mainly focuses on life cycle assessments can also be used as they share the same concept of evaluating products based on different sustainability dimensions, with the CE. De Pascale et al. [145] reviewed 61 different indicators that can be utilized in the presented framework.

In the assessment procedure, the intended goals are defined in the fuzzy logic system with at least three membership functions (Low, Medium, High). Fuzzy rule system is then implemented, and a score is obtained. This process will be further illustrated in section 3.5.

Figure 14: The United Nation's (UN) 17 sustainable development goals [111]

3.5. Collecting Data and Defining Indicators

The assessment procedure is divided into four steps presented in Figure 15. Firstly, users and policy makers determine whether a set of dependent or indented indicators better suit their assessed subject. For dependent indicators or a mix of dependent and independent indicators, fuzzy logic is to be used as illustrated in section 3.5.1.

However, if all indicators are independent (or dependency is not important according to policy makers), then users can directly move to the second stage where weights are assigned to indicators. Like the first step, the CE assessment framework users determine whether policymakers and experts should be involved in the weight's assignment or not.

If weights' assignment is subjective (policymakers and experts' opinions are involved) then the Analytical Hierarchy Process (AHP) is to be used as illustrated in section 3.5.2.1. Otherwise, for objective weight assignment, the entropy method is to be used as presented in section 3.5.2.2. In the third step, the obtained values are normalized using either TOPSIS, GRA or COPRAS methods or using all the three methods for comparison. Finally, results are aggregated, and the alternatives are ordered in descending order of scores and the alternative with the highest score is chosen as the best that fits in a CE.

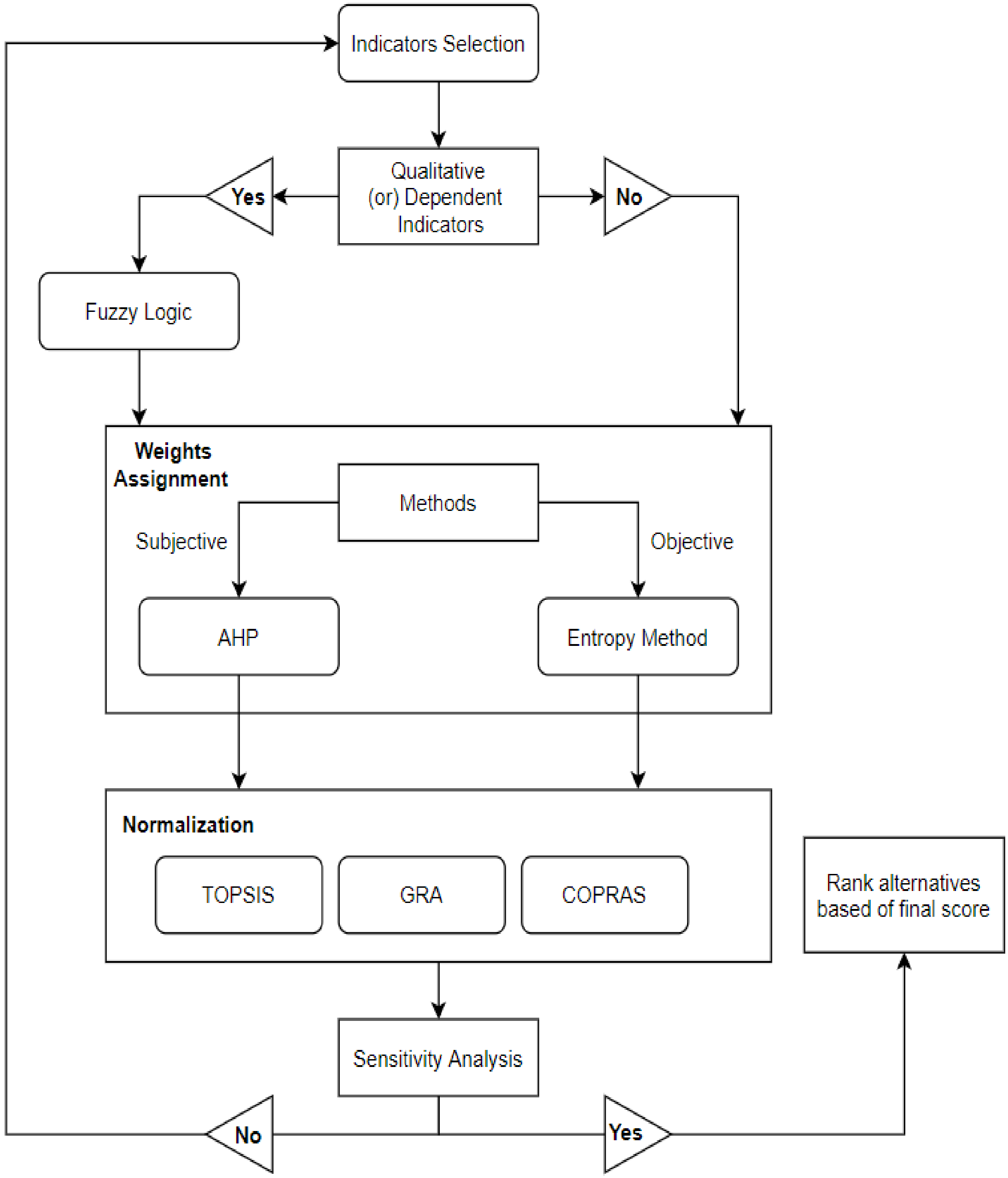

Figure 15: CE Assessment procedure

3.5.1 Fuzzy logic

In this framework, fuzzy logic or fuzzy sets are used as the first step in assessing alternatives based on chosen CE indicators. In general, "*a fuzzy set is a class of objects with a continuum of grades of membership* [146]." On the other hand, in a classical or a crisp set, each member of the set is given a value of one. While nonmembers are given a value of zero as illustrated in the following equation where A represents the crisp set and x represents an element.

$$A\ (x \in A)\ \textbf{or}\ A\ (x \notin A) \tag{1}$$

Then the membership function or sometimes referred to as the characteristic function can be defined as follows:

$$\mu A(x) = 1\ if\ \ (x \in A)\ \textbf{and}\ \ \mu A(x) = 0\ if\ \ (x \notin A) \tag{2}$$

However, in a fuzzy set, an element belongs to a fuzzy set by a degree of membership, where each element is mapped to real numbers between and including zero and one by a membership function as follow [147]:

$$\mu A(x): X \rightarrow [0,1] \tag{3}$$

Where,

$$\mu A(x) = 1 \text{ if } x \text{ is totally in } A \tag{4}$$

$$\mu A(x) = 0 \text{ if } x \text{ is not in } A \tag{5}$$

$$0 < \mu A(x) < 1 \text{ if } x \text{ is partially in } A \tag{6}$$

Hence, this allows a continuum of possible choices [148]. To further explain, $\mu A(x)$ denotes a membership function of set *A* that defines fuzzy set *A* of universe *X*. For example, the element *x* of universe *X* belongs to the set *A* by some degree. This degree carries a value between zero and one and is called the degree of membership that is $\mu A(x)$ [148].

Fuzzy sets can be very handy when dealing with qualitative indicators where membership functions (MFs) can represent these indicators using linguistic terms. For example, consumers' satisfaction level can be described using three MFs such as (Not satisfied, partially satisfied, and very satisfied) along a normalized scale [0,1].

Since the same term may vary in meaning between people, each MF spans over a specific range on the normalized scale. For example, the MF of "Partially satisfied" is a triangular MF spanning from 0.2 to 0.8 as seen in Figure 16. The values assigned and the type (shape) of the membership function can be determined from literature or by experts from the designated fields.

MFs illustrated earlier are called triangular MFs. Depending on the experts, the type of the MF can be changed based on the need and the type of indicator which is done using any fuzzy inference system (FIS). After setting up the indicator (Input) with the desired MFs, experts then setup the output, which are the assessment score.

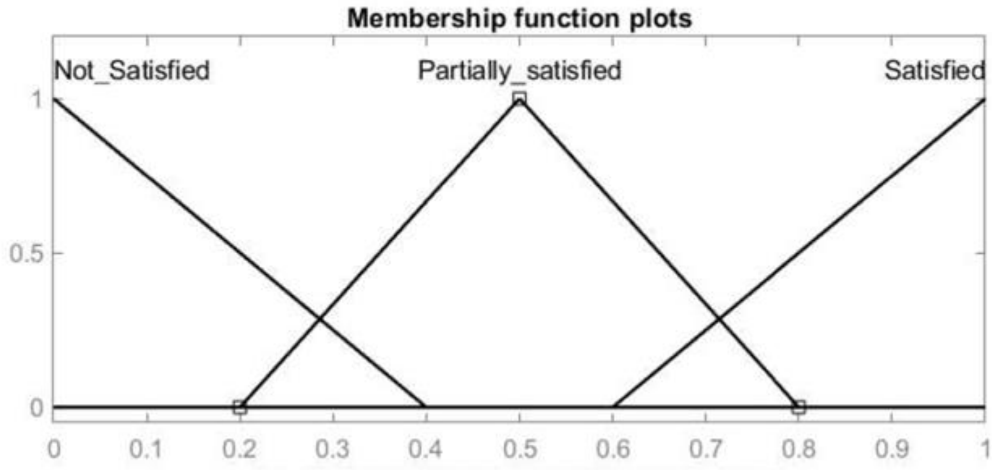

Figure 16: Membership function plots

Similarly, the assessment score (output) can be built using three triangular MFs that are (Low, Average, and High). Consumers' satisfaction level (input) is then linked with the assessment score (output) using a set of rules. The number of rules needed for the FIS is determined using the following equation:

$$n = m^i \tag{7}$$

Where n is the number of rules, m is the number of membership functions and i is the number of inputs. An example of the rules used would be as follow:

1. If consumers' satisfaction level is "**Not Satisfied**" then Score is "**Low**".

2. If consumers' satisfaction level is "**Partially satisfied**" then Score is "**Medium**".

3. If consumers' satisfaction level is "**Satisfied**" then Score is "**High**".

Later, the FIS aggregates and de-fuzzy the system to obtain a result using different aggregation and defuzzification methods that are predefined by the user. The result of the system is a numerical score with its range predefined by the user in the fuzzy inference system (FIS).

In general, fuzzy systems have a strong ability in dealing with uncertainties, it also reduces subjectivity in the assessment of qualitative indicators. Increasing the number of linguistic terms improves the accuracy of the scoring as it provides the users with a wider range of choices that translates to more membership functions and hence, more rules defined in the expert system. Moreover, it allows the implementation of interdependencies across indicators. This can be simply done by adding inputs to the FIS and adjusting the rules based on the interdependencies. For example, there are several indicators corresponding to recycling. End-of-life index, recycling desirability and material circularity, could be selected to represent the recyclability of a product. However, since the three indicators are very similar yet very important, their scores can be easily merged into one score using a rule-based FIS as seen in Figure 17.

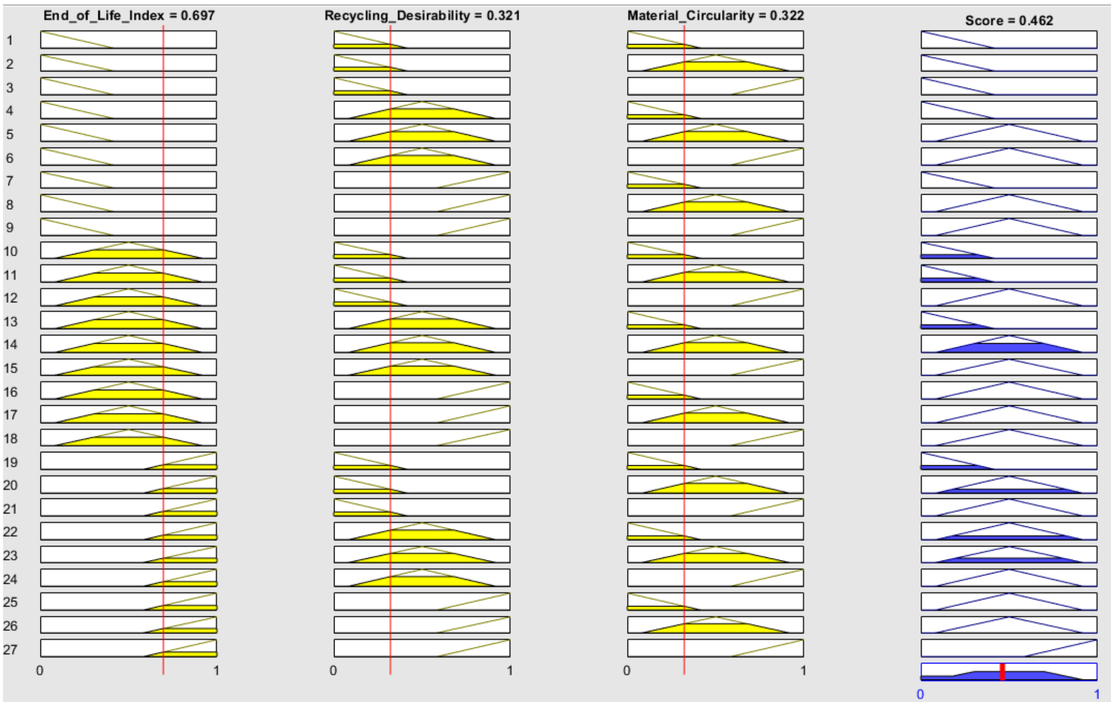

Figure 17: The combination of three interdependent indicators, the end-of-life index set at 0.697, recycling desirability set at 0.3221 and material circularity set as 0.322, each consisting of three membership functions (low, medium, high)

3.5.1.1. Fuzzy inference system

In this proposed framework, it is suggested to use Matlab FIS with its default settings for the (Mandani) method where maximum aggregation technique and center of gravity (COG) method for defuzzification are used.

The previous illustrated procedure is used for every indicator, or to groups of indicators (for interconnections) denoted by $(\boldsymbol{I_1, I_2, I_{...}, I_w})$ where *w* represents the number of indicators or grouped indicators. The results are *n* scores that are denoted as $(\boldsymbol{S_{11}, S_{12}, S_{...}, S_{rw}})$, where *r* is the number of alternatives and *w* is the number of indicators or grouped indicators for the different alternatives denoted as **(A_1, A_2, $A_{...}$, A_r)** where *r* is the number of alternatives. The following sections describes the next steps of assigning weights, normalization and obtaining the final CE score of the different alternatives.

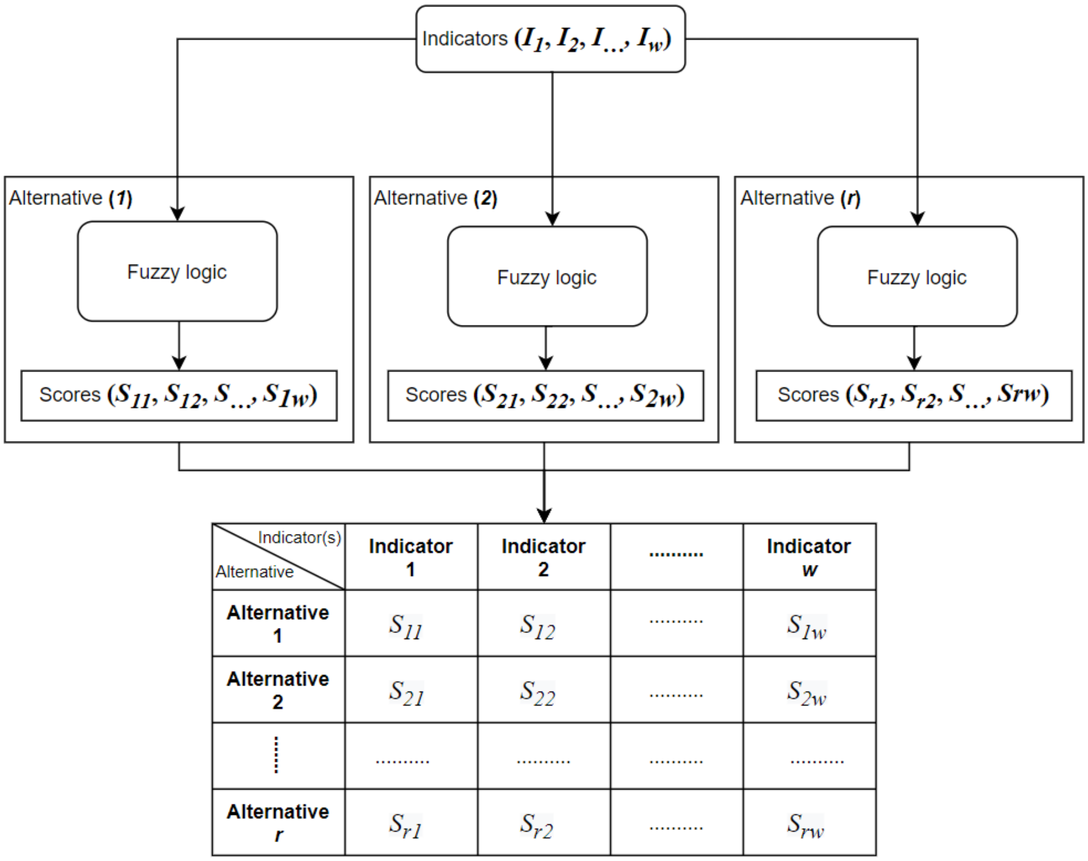

Figure 18: Score matrix obtained using fuzzy logic

3.5.2 Assigning weights to indicators

The next step is to assign weights to each indicator. Weights can be determined using subjective and objective weight defining methods. Several weighing techniques can be used while implementing the CE assessment framework. For example, if experts' opinions on the indicator is an important factor to the framework users, then a subjective weight determination method such as the analytical hierarchy process (AHP) or the analytical network process (ANP) are used. On the other hand, if the CE framework users are to avoid subjectivity, then objective wight determination methods are to be used such as the entropy method. Another possible approach is using a combination of both subjective and objective methods.

3.5.2.1. *Analytical hierarchy process (AHP)*

The AHP generally consists of three main steps namely, decomposition of the problem, comparative judgment, and generation of priorities [149]. The main aim of the AHP method is to develop a hierarchical structure with the main goal at the top level, the criteria, or attributes (Indicators) are placed at the second level and the alternatives at bottom level. For this framework, no priorities are generated since the AHP method is used to define weights only. The first step in the AHP is to build an importance matrix P_{AHP} (w*w) with the indicators aligned in the first row and the first column in the same order as seen in Figure 19.

	Indicator 1	**Indicator 2**	**Indicator *w***
Indicator 1	1	1/a	1/b
Indicator 2	a	1	1/c
Indicator *w*	b	c	1

Figure 19: AHP Importance Matrix

Policymakers and experts then decide the comparative relative importance of among indicators. Same indicators will have a relative importance of 1 as illustrated in the importance matrix in Figure 19. Other indicators are given a number from 2 to 9 and reciprocals are given to same indicators when order is switched as seen in Table 6.

Table 6: AHP intensity of importance table [149]

Intensity of Important	Definition
1	Equal Importance
3	Moderate Importance
5	Strong Importance
7	Very Strong Importance
9	Extremely Important
2,4,6,8	For the intermediate values
Reciprocals	For vice versa Comparison, if i to j is 3, then j to i is 1/3

These values represent the relative importance of one alternative when compared to other keeping one indicator fixed [150]. A normalized element is then obtained using the following equation:

$$r_{ij} = \frac{p_{ij}}{\sum_{i=1}^{w} e_{ij}} \quad (8)$$

Where p_{ij} is an element of the original matrix P_{AHP} (w*w) and the denominator is the summation of all the elements in the respective column. Finally, the weight vector is obtained using the following equation:

$$\boldsymbol{w} = \frac{1}{N \sum_{i=1}^{N} r_{ij}} \quad (9)$$

Where N is the number of alternatives [150].

3.5.2.2. Entropy method (objective).

As mentioned earlier the entropy method is used when objective assessment is required as it assigns weights based on the indicator's real value [151]. The first step is the normalization of the fuzzy score matrix obtained in figure (8). This is done using the following equation:

$$N_{rw} = (S_{rw}) / (\sum_{r=1}^{n} S_{rw}) \quad (10)$$

Where N_{rw} are the normalized values and n is the number of alternatives. The following step is computing the entropy value using the following equation:

$$e_w = -h \sum_{r=1}^{n} N_{rw} \ln N_{rw} \quad (11)$$

Where $h = \frac{1}{\ln(n)}$. Finally, the weight vector is computed as follow:

$$\boldsymbol{w}_r = \frac{1-e_w}{\sum_{r=1}^{m}(1-e_w)} \quad (12)$$

3.5.3 Assigning weights to indicators

Weight vectors obtained through either the AHP or the entropy method is then applied to the normalized matrix obtained after applying either the TOPSIS, GRA, or the COPRAS methods. Also, all three methods could be applied, and the final results are compared to validate the final choice.

3.5.3.1. Grey relation analysis (GRA)

The GRA is a quantitative method that help in decision making based on the degree of relation between two different sequences. Results of this method is obtained by testing the degree of difference or the degree of similarity between the sequences [152].

The GRA mainly consists of four steps. Firstly, the grey relation generating followed by the reference sequence definition, grey relation coefficient calculation and lastly, grey relation grade calculation [153].

1. Grey relational generating

The first step is the grey relation generation in which the attributes are all scaled into [0,1] using the following equation:

$$x_{ij} = \frac{y_{ij} - Min\{y_{ij}, i = 1,2, \dots, r\}}{Max\{y_{ij}, i = 1,2, \dots, r\} - Min\{y_{ij}, i = 1,2, \dots, r\}} \tag{13}$$

for $i = 1, 2, \dots, r \quad j = 1,2, \dots, w$

Where r is the number of alternatives and w is the number of indicators. Since all scores obtained from the fuzzy logic, they are considered beneficial values, i.e. preferred to be larger.

2 Reference sequence definition

The reference square definition step aims to find an alternative whose values are the closest to one for all of its performance values. However, since this will rarely be the case, a reference sequence X_0 is defines as $(x_{01}, x_{02}, \dots, x_{0j}, \dots, x_{0n}) = (1,1,\dots,1,\dots,1)$, and then aims to find the alternative whose comparability sequence is the closest to the reference sequence [153]

3 Grey relational coefficient calculations

In this step the grey relation coefficient is calculated, this is basically the closeness of x_{ij} to x_{0j} where the greater the grey relation coefficient the closer their values are. This coefficient is calculated using the following equation:

$$\gamma(x_{0j}, x_{ij}) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{ij} + \zeta\Delta_{\max}} \tag{14}$$

for $i = 1, 2, \dots, r \quad j = 1, 2, \dots, w$

Where $\gamma\left(x_{0j}, x_{ij}\right)$ is the grey relation coefficient between x_{ij} and x_{0j} and,

$$\Delta_{ij} = |x_{ij} - x_{0j}| \tag{15}$$

$$\Delta_{\min} = Min(\Delta_{ij}, i = 1, 2, \dots, r; j = 1, 2, \dots, w) \tag{16}$$

$$\Delta_{\max} = Max(\Delta_{ij}, i = 1, 2, \dots, r; j = 1, 2, \dots, w) \tag{17}$$

ζ is used to enlarge or compress the range of the grey relation coefficient and is called the distinguishing coefficient.

4 Grey relational grade calculations

The final step of the GRA method is to calculate the grey relation grade to obtain a single index that is used to rank the alternatives. This is done using the following equation:

$$\Gamma(X_0, X_i) = \sum_{j=1}^{n} w_j \gamma(\, x_{0j} - x_{ij}) \text{ for } i = 1, 2, \dots, r) \tag{18}$$

$\Gamma(X_0, X_i)$ represents the level of similarity between the comparability sequence and the reference sequence, while $\boldsymbol{w_j}$ is the weight of the indicator *j* that take numbers from 1 to w (number of indicators) that is previously found using either the AHP or the entropy method.

3.5.3.2. Technique for order preference by similarity to the ideal solution (TOPSIS)

The first step in the Technique for order preference by similarity to the ideal solution (TOPSIS) is normalization of the score matrix using the following equation:

$$\bar{x}_{rw} = \frac{x_{rw}}{\sqrt{\sum_{w=1}^{m} x_{rw}^2}} \tag{19}$$

Where *m* is the number of alternatives. Next, the weight of each indicator is multiplied by the normalized alternative values to obtain the weighted normalized decision matrix (WNDM). Using the WNDM, the ideal best (V_w^+) and the ideal worst (V_w^-) which are the best and worst scores respectively are obtained for each indicator.

The next step is calculating the Euclidean distance from the ideal best (S_r^+)and ideal worst (S_r^-) using the following equations:

$$S_r^+ = \left[\sum_{w=1}^{m}(V_{rw} - V_w^+)^2\right]^{0.5} \quad (20)$$

$$S_r^- = \left[\sum_{w=1}^{m}(V_{rw} - V_w^-)^2\right]^{0.5} \quad (21)$$

Finally, the performance score is calculated using the following equation:

$$P_r = \frac{S_r^-}{S_r^+ + S_r^-} \quad (22)$$

The alternatives are then ranked based on their scores where the highest score is ranked as the best alternative and the second highest as the second and so on.

3.5.3.3. Complex proportional assessment method (COPRAS)

s Another possible method of finding the final CE assessment score is the COPRAS method. It is an easy-to-use method that consists of 7 simple steps described below:

Step (1) The decision matrix is prepared in the following format:

$$X = \begin{bmatrix} m_{11} & m_{12} & \cdots & m_{1w} \\ m_{21} & m_{22} & \cdots & m_{2w} \\ \vdots & \vdots & \cdots & \vdots \\ m_{r1} & m_{r2} & \cdots & m_{rw} \end{bmatrix} \quad (23)$$

Note that the decision matrix is the fuzzy logic score matrix obtained in Figure 18 where *r* is the number of alternatives and *w* is the number of indicators.

Step (2) Normalization of the decision matrix

The decision matrix is then normalized using the following equation:

$$\bar{x}_{ij} = \frac{m_{ij}}{\sum_{i=1}^{r} m_{ij}} \ ; i = 1, 2, \ldots, r \text{ and } j = 1, 2, \ldots, w \quad (24)$$

Step (3) Weighted normalized value calculation

The next step is calculating the weighted normalized value using the weights obtained in section (5.2) using the following equation:

$$\hat{x}_{ij} = \bar{x}_{ij} \times \boldsymbol{w}_j; i = 1, 2, \ldots, r \text{ and } j = 1, 2, \ldots, w \quad (25)$$

Step (4) Sum P_i calculations

$$P_i = \sum_{j=1}^{k} \hat{x}_{ij} \tag{26}$$

Where P_i is the relative weight of each process.

Step (5) determine the optimality criterion

$$K = max P_i; i = 1, 2, \dots, r \tag{27}$$

Step (6) Utility degree

Calculating utility degree is done using the following equation:

$$N_i = (P_i / P_{max}) \times 100\% \tag{28}$$

Step (7) Ranking

The final step is ranking the process in descending order based on the values obtained from step (6).

Chapter 4. Case Study

The presented framework developed in Chapter 2 is implemented to assess the circularity of Friction Stir Back Extrusion (FSBE), an "extrusion process is a manufacturing process used to produce fine grained tubular structures based on severe plastic deformation", against conventional extrusion methods [29, 154]. The investigation will be carried out on Mg AZ31 tubes.

4.1. Procedure

The first step is to select applicable indicators as described in section 3.4 while making sure all indicators are applicable to the selection criteria illustrated in section 3.3. The intention of this assessment is to test the circularity of a process, which falls under the description of a micro-level process. Hence, possible choices of micro-level indicators may be the carbon dioxide emissions, energy cost, and labour cost. Also, since the FSBE is a manufacturing process, the industry indicators selected are related to the final manufactured product which are the toughness, ultimate tensile strength, yield strength and ductility. The CE indicators chosen are production speed, job satisfaction, injury rate and energy consumption. Lastly, the main goal achieved by the FSBE is mainly the 9th SDG. All indicators selected are summarized in Figure 20.

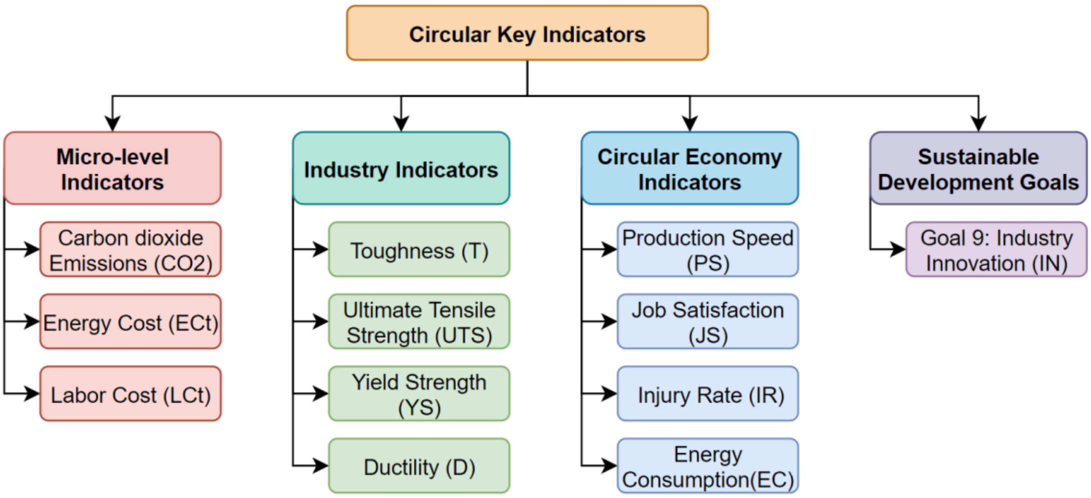

Figure 20: Selected circular key indicators

The next step is applying fuzzy logic since the indicators are qualitative and quantitative. Three membership functions are defined for each indicator which are: low, medium, and high. An example of the indicators membership functions as well as the scales used is presented in Figure 21 and the values assigned are presented in Table 7.

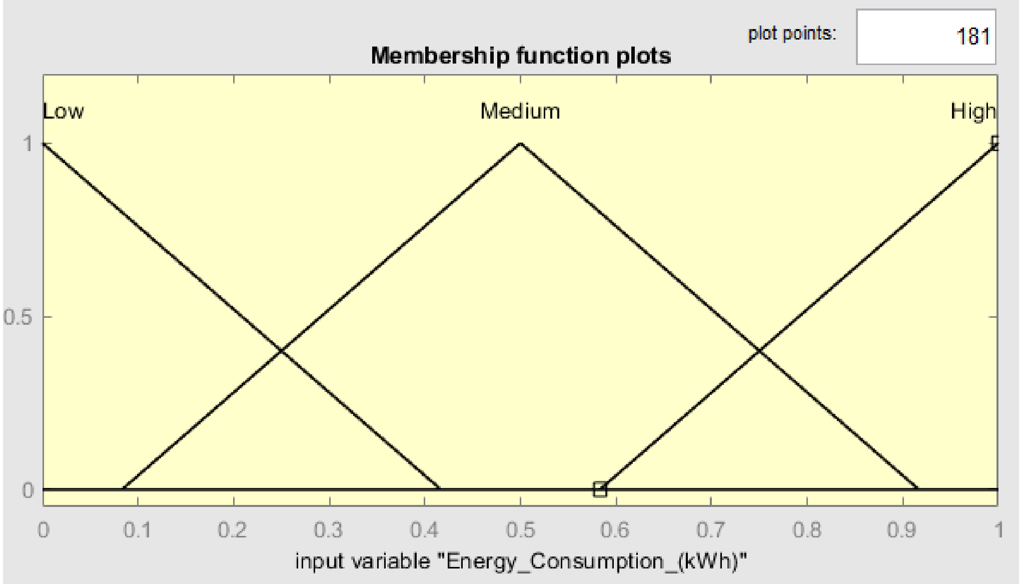

Figure 21: Membership functions of the Energy Consumption indicator with a range of [0 1] (kWh)

Table 7: List of indicators used in the assessment and the ranges used

Indicator	Membership Functions	Range
Carbon dioxide Emissions (Kg)	Low – Medium – High	0 - 1
Energy Cost (fils)	Low – Medium – High	0-50
Labor Cost ($/hr)	Low – Medium – High	5-35
Toughness (J/mm^3)	Low – Medium – High	5-60
Ultimate Tensile Strength (Mpa)	Low – Medium – High	50-500
Yield Strength (Mpa)	Low – Medium – High	100-200
Ductility (%)	Low – Medium – High	0-100
Production Speed (mm/min)	Low – Medium – High	0-500
Job Satisfaction ($/hr)	Low – Medium – High	10-30
Injury Rate (injury per 10000 worker)	Low – Medium – High	0-1000
Energy Consumption (kWh)	Low – Medium – High	0-1
SDGs		0-1

The indicators are quantified using different quantification methods as highlighted in literature [29, 154, 155]. The values obtained are presented in Table 8.

Table 8: Indicator's values for extrusion and FSBE [29]

Process	Indicators											
	CO2 (Kg)	ECt (fils)	LCt ($/hr)	T (J/mm^3)	UTS (Mpa)	YS (Mpa)	D (%)	PS (mm/min)	JS ($/hr)	IR	EC (kWh)	SDG (9)
Extrusion	1	24.8	18.7	17.7	220	180	8.3	360	18.7	370	1	0
FSBE	0.04	1	21.3	42.7	327	175	13.8	90	21.3	38.5	0.045	1

4.2. Results

Values are entered to the FIS in Matlab and the following results are obtained:

Table 9: Fuzzy Scores obtained using Matlab FIS

Process	Indicators											
	CO2 (Kg)	ECt (fils)	LCt ($/hr)	T (J/mm^3)	UTS (Mpa)	YS (Mpa)	D (%)	PS (mm/min)	JS ($/hr)	IR	EC (kWh)	SDG (9)
Extrusion	0.136	0.5	0.507	0.448	0.489	0.634	0.14	0.561	0.507	0.27	0.136	0
FSBE	0.863	0.864	0.5	5.05	0.509	0.584	0.279	0.341	0.5	0.86	0.863	1

The next step is assigning weights to the indicators. This is done using the entropy method and the weights obtained for each indicator are as follow:

Table 10: Weights obtained using entropy weight method

Indicator	CO2 (Kg)	ECt (fils)	LCt ($/hr)	T (J/mm^3)	UTS (Mpa)	YS (Mpa)	D (%)	PS (mm/min)	JS ($/hr)	IR	EC (kWh)	SDG (9)
Weights	0.742	0.0548	3.49E-05	0.00258	0.00029	0.00121	0.088	0.0453	3.49E-05	0.260	0.742	1.41

Lastly, by implementing the GRA method for normalization and aggregation, the following circularity scores are obtained per indicators' set:

Table 11: Final CE scores obtained using GRA method

Process	Indicators' Sets				
	Level	Industry	Circular	SDGs	Circularity Score (Average)
Extrusion	0.0885	0.00788	0.0948	0	0.0478
FSBE	0.265	0.0228	0.254	1.41	0.489

The results show a better circularity for the FSBE over conventional extrusion. Hence, FSBE is the better option for extrusion processes in manufacturing facilities compiling with or aiming to be a part of the CE. Also, it can be noticed that the impact of SDGs is made evident in the developed framework. Taking SDGs into consideration is an important factor in determining the circularity of any process or a product due to their comprehensive criteria that covers almost all dimensions of sustainable development. Hence, circularity cannot be achieved without achieving at least one SDG. Removing SDGs from the assessment procedure lowers the circularity score of the FSBE from 0.490 to 0.181 and increases the extrusion's score from 0.048 to 0.064. hence, when comparing circularity alternatives that achieve different SDGs are given a higher score compared to others that do not achieve any.

Chapter 5. Conclusion and Future Work

This thesis presented a review on the implementation and integration of CPSs in each of the CE stages, highlighted the SDGs that would be achieved as a result, and reviewed the current state of the CE assessment tools. The findings on the implementation of CPSs in the CE are presented below:

- All six stages of the CE have a great potential to integrate CPSs within them.
- Autonomous mining in the sourcing stage provides a safe and efficient working environment and achieves five different SDGs.
- There are many possible implementations of CPSs in the design stage, such as in design information feedback systems, in testing and simulation assistance in product designs, and in designs for manufacturing and assembly. These systems directly achieve five SDGs and indirectly achieve two SGDs.
- The impact of CPSs in the manufacturing stage is enormous with vast room for implementation, such as in smart factories, QC and QA, health monitoring of machines and products, and many more. More than half of the SDGs can be achieved through the implementation of different CPSs in this stage.
- The integration of CPSs in the distribution stage can result in several implementations, such as the development of the path decision ant algorithm, UAVs, and virtual data communication platforms. Together, these applications contribute to seven different SDGs.
- In the usage stage, the implementation of CPSs can be at the product level or the consumer level. Some of these applications include adaptable electronics and portable health monitoring devices. Four different SDGs are achieved through the applications presented.
- Using RFID in recycling would facilitate the connection between this stage and different stages along the CE. On its own, it achieves five different SDGs.

Moreover, it is critically important to establish an assessment tool and a monitoring structure to ease processes and products' progresses measurability towards circularity. Many factors should be taken into consideration when establishing comprehensive assessment tools such as the ability to conduct the assessment on a micro, meso, and macro levels. Hence, the proposed CE assessment framework in Chapter 3 presents a step-by-step indicators selection procedure that would allow a flexible choice of indicators while maintaining the CE model structure. Simultaneously, it mitigates flaws within indicators and produce credible assessment scores by involving different dimensions and scales within the CE.

Different MCDM methods are involved in the CE assessment framework, where two pathways are demonstrated. Also, Fuzzy logic was incorporated in the assessment procedure. The assessment framework proposed has the following capabilities:

- Assessing the circularity of developed and developing countries, different industries, and numerous processes and products whether it is for private or public sectors.
- Assessing the circularity on different levels (Micro, Meso, and Macro).
- It offers users flexibility in defining indicators while limiting uncertainties that arise from the linguistic variables used.
- The rule-based expert system presented allows policymakers and experts to apply their knowledge and expertise throughout the assessment procedure.
- Depending on the preferences of the stakeholders, the framework allows subjective, and objective means of weight assignment to the indicators. As a result, the scores can be influenced throughout the different assigned fuzzy rules and MCDM methods used if needed.

This gives the demonstrated framework a wide scope of applications that ranges from internal audits to facilities, processes, and products' planning and designs on different levels.

Lastly, to validate the proposed framework, a case study was conducted in Chapter 4 to compare the circularity of FSBE to conventional extrusion processes. The results showed that FSBE fits better in a CE than conventional extrusion scoring 0.490 and 0.0478 respectively. The scores also demonstrated the importance of SDGs when it comes to circularity which further validates the proposed framework that aims to highlight the importance of achieving SDGs.

As future work, it is important to establish indicators' databases by experts of different industries to support and ease the transition to CE. Furthermore, there is a need to provide a similar review on other I4.0 tools as these technologies have wide applications and capabilities that have not been fully investigated on the CE scale. Also, to further improve the demonstrated CE assessment framework, engaged governments, organizations, and policymakers are encouraged to standardize different sets of indicators based on their leading domestic industries to involve local expertise. Moreover, there should be different means of data sharing platforms to establish international sets of indicators for global processes and products to ease assessment procedures. Also, the time factor is suggested to be included within indicators to give an updated circularity score for time-dependent variable indicators.

To further enhance the credibility and reliability of the CE tool's circularity results, the micro, meso, and macro levels should be all taken into consideration. Unlike the example used earlier, a more comprehensive product would not give realistic results if their indicators were not fully explored, or in other words, indicators do not cover all the framework stages mentioned earlier. A promising example would be assessing the circularity of the automotive industry. This can be conducted on three types of vehicles that are: conventional internal combustion engine vehicles, battery electric vehicles, and fuel cell electric vehicles. Such an assessment would open many research areas by pointing out different zones of improvements along and beyond vehicles' life cycles.

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Vita

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