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Master's Programme in Manufacturing

Life Cycle Analysis (LCA) applied to the calculation of environmental impacts of Metal Additive Manufacturing Processes

Direct Energy Deposition – Wire & Arc Additive Manufacturing (DED-WAAM)

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Master’s thesis
2025

Aalto-yliopisto
Aalto-universitetet
Aalto University

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Title of thesis Life Cycle Analysis (LCA) applied to the calculation of environmental impacts of Metal Additive Manufacturing Processes

Programme Master Program in Manufacturing

Major Zero Defect Manufacturing for a Circular Economy

Thesis supervisor Prof. Mika Salmi

Thesis advisor(s) Prof. Mika Salmi

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Date 24.09.2025 **Number of pages** 63 **Language** English

Abstract

Wire Arc Additive Manufacturing (WAAM) belongs to the family of Direct Energy Deposition (DED) processes. It uses a metallic wire feedstock melted by an electric arc to build components layer by layer. The method is increasingly recognized for combining high material efficiency, geometric flexibility, and rapid deposition rates, making it attractive for large-scale parts in sectors such as aerospace, automotive, and heavy machinery.

Despite these advantages, the environmental performance of WAAM is not yet fully characterized due to the limited availability of reliable process-specific inventory data. To address this gap, this study develops a preliminary methodology for constructing life cycle inventory (LCI) datasets for WAAM, coupled with uncertainty or reliability assessment of these data using a pedigree matrix approach. Based on this, an LCA model was implemented using empirical process data collected at the Addimadour Additive Manufacturing Solutions platform.

The key contribution of this work lies in the development of a detailed process tree that maps the inventory for all relevant unit processes, ranging from pre-processing, deposition, and post processing. In addition to this, the application of a pedigree matrix to quantify uncertainty in each inventory dataset provides a more accurate and data-driven representation of the WAAM LCA inventory. The system boundary covered substrate preparation, wire feedstock deposition, shielding gas usage, and associated electricity inputs. The inventory was modelled using the SimaPro software and the Ecoinvent v3 database, with a functional unit defined as 1 kg of net printed part.

LCA results indicate that the substrate material and shielding gas are dominant contributors across most environmental impact categories (midpoint impact categories), including Global Warming Potential, Acidification, and Resource Scarcity. These results are consistent with literature while highlighting current data quality limitations in AM-LCA studies. The work also identifies opportunities for improving environmental performance through process optimization and emphasizes the need for in-situ monitoring to generate higher-resolution LCI data for future WAAM LCA studies. This thesis contributes to bridging the gap between academic LCA models and industrial-scale, data-driven assessments of metal additive manufacturing.

Keywords Wire Arc Additive Manufacturing (WAAM), Direct Energy Deposition (DED), Life Cycle Assessment (LCA), Unit Process Tree Approach, Pedigree Matrix, In-situ data monitoring.

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Preface and acknowledgements

This master's thesis journey was a blend of wonderful experiences and new challenges, marked by the inevitable ups and downs. It was, therefore, not a solitary path, and I would like to express my deepest gratitude to Prof. Laurent Terrenoir and Prof. Laura Laguna Salvadó, my academic supervisors at ESTIA Institute of Technology, for their valuable guidance, continuous support, and encouragement throughout the course of this work. Additionally, I am sincerely thankful to Mr. Pierre Michaud and the entire Addimadour team (primarily Anaïs and Stivell) for granting me access to the manufacturing cell and assisting with technical data collection during the experimental phases. I also extend my appreciation to ESTIA Research for hosting this study, and to my colleagues and friends (Georgia, Saioa and Romain) for their insights, conversations and motivation.

A notable mention goes to Prof. Olivier Kerbrat from the Rennes Institute of Physics at ENS Rennes. His expert advice on manufacturing processes, inventory modelling, and process tree methodology contributed significantly to the success of this work. Appreciation is also extended to my Grenoble INP tutors, Prof. Pascal Robert and Sarah Bensrhir who also occasionally contributed to my work during our monthly meetings. I acknowledge Aalto University (Finland), School of Engineering for granting me admission to their EIT Manufacturing joint master's in manufacturing and industrial engineering (Zero Defect Manufacturing for a Circular Economy), and to Prof. Mika Salmi of the School of Engineering for his support in my work.

Finally, my heartfelt gratitude goes to my family in Kenya (my parents and siblings) as well as to my relatives living in USA, Finland, Luxembourg, and South Africa, whose academic journeys abroad have always inspired me. My parents' unwavering support and belief in my pursuit of sustainable engineering research have been a constant source of strength and motivation. Last but not least, I would like to thank Timothy Tonui and Alice Joan, my peers from undergraduate studies, with whom I remained closely connected throughout my stay in France. To all those whose influence may not be explicitly mentioned but have contributed to my journey in various ways, from casual conversations to discussions, I extend a big thank you. Asanteni sana!

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01 September 2025

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Symbols and abbreviations

Symbols

U_T	Total uncertainty
U_b	Basic uncertainty
U_i	Uncertainty factor for each pedigree criterion
Σ	Sum
Kg	Kilogram
Sgd95	Standard geometric deviation covering 95% of the data

Operators

exp	Exponential function
ln	Natural logarithm

Abbreviations

AM: Additive Manufacturing

WAAM: Wire and Arc Additive Manufacturing

DED: Direct Energy Deposition

MAM: Metal Additive Manufacturing

DED-LP: Direct Energy Deposition – Laser Powder process

DED-EB: Direct Energy Deposition – Electron beam process

DED-PA: Direct Energy Deposition – Plasma Arc process

DED-GMA: Direct Energy Deposition – Gas Metal Arc process

DED-WAAM: Direct Energy Deposition – Wire Arc Additive Manufacturing

CMT: Cold Metal Transfer

CED: Cumulative Energy Demand

LCA: Life cycle analysis/assessment

LCI: Life cycle inventory

LCIA: Life cycle impact assessment

1 Introduction

1.1. Background

In recent years, industrial progress has led to significant improvements in fast and good quality manufacturing and production (Cardoso Reis et al., 2023; Kokare, Godina, et al., 2023). However, industrialization has proven to be a great contributor to the associated negative effects to climate and environment. Impacts related to manufacturing and production, whether these are environmental, economic or social have often gone understudied or neglected. The manufacturing sector is one of the most polluting sectors (Kokare, Oliveira, et al., 2023). The 5th IPCC report indicated that manufacturing accounts for 28% of final energy use and 13 gigatonne carbon dioxide equivalent emissions. These figures are expected to increase up to 150% by the year 2050 should energy efficiency improvements derails (Mitchell, 2017).

This has pushed both industry professionals and researchers to look for production methods that are better for the environment while still keeping product quality high and meeting delivery deadlines. Whereas, conventional manufacturing methods have existed since the industrial revolution, additive manufacturing (AM) is a newer method which promises reduced material consumption, ability to produce parts with complex geometries, repair damaged parts, etc. (Balidas et al., 2024b).

The emerging trend of metal additive manufacturing is keenly focused on increased environmental sustainability and productivity, which involves reformation of production cycle, increased the life of working tools, reducing the design complexity, etc. (Rajaguru et al., 2020). Metal Additive Manufacturing processes follow the same concept of Additive manufacturing which produces products that are digitally manufactured from their 3D design data in a layer-by-layer manner (Balidas et al., 2024b; Dias et al., 2022; Mika & Pei, 2023). Among different additive manufacturing techniques, Wire Arc Additive Manufacturing (WAAM) shows the best energy performance. Research examining various process settings reveals that the speed at which material is deposited significantly affects how much energy the process uses (Balidas et al., 2024b). In addition, WAAM process has shown a significant reduction of total primary energy demand with respect to the conventional processes (Campatelli et al., 2020). Comparison studies between metal additive manufacturing and conventional manufacturing processes like in Hadjipantelis et al., 2023 study have shown that for the production of steel beams, WAAM leads to lower impacts in environmental impact categories than on an I-beam produced using hot-rolling process. Many studies argue that, in general, metal additive manufacturing processes have the potential to be more environmentally sustainable than conventional manufacturing methods (Kokare, Oliveira, et al., 2023; Reis et al., 2023).

1.2. Research Question

Despite the promising potential of Direct Energy Deposition (DED) technologies like Wire Arc Additive Manufacturing (WAAM) to reduce environmental impact compared to conventional methods, reliable and process-specific Life Cycle Inventory (LCI) data remains scarce. Most existing studies are based on theoretical assumptions or use non-representative part geometries, which limit the applicability of results to industrial contexts. Furthermore, current LCA studies often lack real-time, accurate process-specific data. This creates uncertainty in environmental impact assessments and hinders the formulation of accurate eco-design strategies. A data-driven, unit process-level LCA model, built using monitored inputs from actual manufacturing environments, is thus essential to establish a more credible environmental baseline for WAAM. This raises the central research question for this work:

"How can accurate and reliable inventory data for the DED-WAAM process be generated to support robust and complete life cycle assessments?"

1.3. Objective(s) of the Study

This thesis aims to address the lack of accurate and reliable inventory data for the DED-WAAM process, in order to enable a data-driven life cycle assessment (LCA) of the environmental impacts associated with manufacturing a part using the WAAM process. This work will result to a more robust understanding of the material, energy, and emission flows associated with DED-WAAM, while identifying critical impact drivers and data quality gaps in current modelling practices.

1. **To characterize the DED-WAAM process chain** from substrate preparation, deposition, to post-processing, and define system boundaries suitable for LCA.
2. **To quantify the material and energy flows** involved in the process using direct measurements, sensor data, and standardized assumptions where necessary.
3. **To model the process inventory** in SimaPro using Ecoinvent v3 and apply midpoint and endpoint impact assessment methods.
4. **To explore the role of in-situ monitoring** and propose improvements for LCA data accuracy in future WAAM studies.
5. **To provide recommendations** for improving environmental performance in WAAM systems and identifying perspectives for future work, including instrumentation and dynamic LCA.

1.4. Structure of the thesis

This thesis is organized into five main chapters. Chapter 1 introduces the background, problem definition, and objective of the study, providing a foundation for understanding the research context. Chapter 2 presents a comprehensive literature review covering wire arc additive manufacturing (WAAM), life cycle assessment (LCA), and the current gaps in reliable inventory data for the DED-WAAM process. Chapter 3 describes the research methodology, detailing the process tree modelling approach, system boundaries, data collection methods, and the LCA framework applied. Chapter 4 focuses on results and discussion, where experimental findings, inventory data, environmental impact assessments, and comparative analyses with existing datasets are presented and critically examined. Finally, chapter 5 concludes the work by summarizing key contributions, highlighting limitations, and proposing recommendations and future research perspectives, particularly in integrating in-situ data monitoring.

2. Literature review

Additive manufacturing, originally developed in the mid-1980s, for many it is seen as a polymer-based technology; while this is true, with new developments in CAD/CAM and laser and wire technology, AM has moved into the metal arena (Herzog et al., 2016; Pérez et al., 2020). The ISO/ASTM 52900 standard classifies additive manufacturing in 7 process categories: Material extrusion (MEX), Powder bed fusion (PBF), Material jetting (MJ), Vat photopolymerization (VP), Binder jetting (BJ), Direct Energy Deposition (DED), and Sheet lamination (SL) (Ituarte et al., 2015; Mika & Pei, 2023).

When focusing specifically on metal production, these technologies narrow down to two primary approaches. Powder bed fusion (PBF) and Direct energy deposition (DED) represent the dominant methods for metal additive manufacturing according to ISO/ASTM 5290 standards (Ding et al., 2015).

2.1. Wire and Arc Additive Manufacturing (WAAM)

According to the ISO/ASTM 52900:2021 standard, direct energy deposition (DED) as an additive manufacturing process using focused thermal energy (such as a laser, electron beam, or plasma arc) to fuse materials (powder or wire) by melting as they are being deposited (ISO / ASTM 52900, n.d.). Like powder bed fusion, DED-based processes work well for creating intricate components but need an inert environment to prevent oxidation (J. Liu et al., n.d.). According to the feedstock commonly used, either in the form of powder or wires, DED can have the following nomenclature: DED-LP, DED-WAAM, DED-EB.

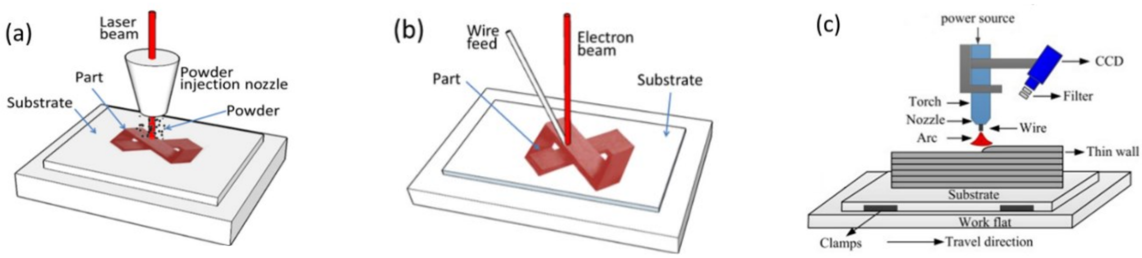

Figure 1. Schematic illustration of (a) DED-LP, (b) DED-EB, (c) DED-WAAM (DebRoy et al., 2018)

Figure 1 illustrates three different types of direct energy deposition methods. Part 1a displays a DED-LP setup that uses powder as its raw material. In this approach, powder gets fed directly into the melting zone and liquid metal pool generated by laser heating. The DED-EB technique shown in 1b employs an electron beam to build deposits by introducing commercial wire into the heated pool. This process requires a large vacuum chamber to maintain clean conditions throughout manufacturing and cooling phases. Part 1c demonstrates the DED-WAAM approach, which uses electrical arc heating combined with wire feedstock, similar to standard welding methods. Protective gases like argon prevent the heated metal from reacting with air during processing (DebRoy et al., 2018). The WAAM technique has historical roots dating back to 1925, when American inventor R.Baker suggested using arc heating with wire materials to create decorative metal items (Baker, 1920).

2.1.1. Different forms of WAAM deposition process

Based on their heating methods (Table 1), GMAW creates an electrical arc between a wire that gets consumed during the process and the base material. In contrast, GTAW and PAW rely on tungsten electrodes that don't get used up during welding. The wire positioning in GMAW typically runs straight down to the surface, while the other two techniques allow different wire angles, which influences deposit quality and makes process design more challenging (Ding et al., 2015).

Table 1. Comparison of various WAAM techniques (Ding et al., 2015)

WAAM	Energy source	Features
GTAW-based	GTAW	Non-consumable electrode; Separate wire feed process; Typical deposition rate: 1-2 kg/hour; Wire and torch rotation are needed;
GMAW-based	GMAW	Consumable wire electrode; Typical deposition rate 3-4 kg/hour; Poor arc stability, spatter;
	Cold metal transfer (CMT)	Reciprocating consumable wire electrode; Typical deposition rate: 2-3 kg/hour; Low heat input process with zero spatter, high process tolerance;
	Tandem GMAW	Two consumable wires electrodes; Typical deposition: 6-8 kg/hour; Easy mixing to control composition for intermetallic materials manufacturing ;
PAW-based	Plasma	Non-consumable electrode; Separate wire feed process; Typical deposition rate 2-4 kg/hour; Wire and torch rotation are needed;

2.1.2. Cold Metal Transfer (CMT) Welding in Metal Additive Manufacturing

CMT welding uses wire movement control systems that digitally coordinate how the wire moves with droplet formation through its mechanical design. Research shows that CMT provides reduced heat input while maintaining stable arc performance (Li et al., 2022). The main components of CMT-WAAM equipment include the arc heating system, positioning table, wire delivery mechanism, rotating table, and protective gas unit (Fang et al., 2019).

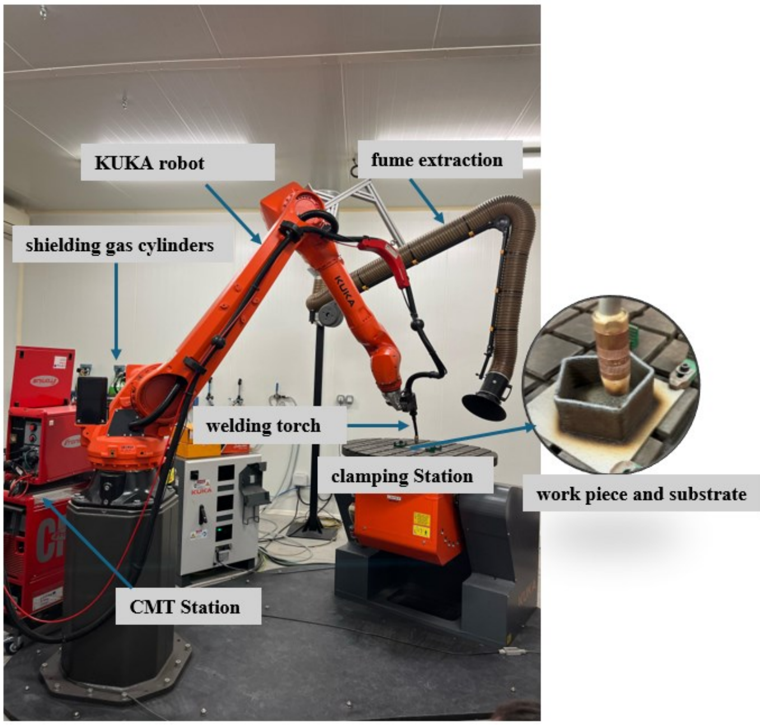

Figure 2. The hardware of CMT-WAAM (Addimadour)

2.1.3. WAAM Process Steps

Research by Singh & Khanna (2021) identifies three essential stages in WAAM part production: initial setup and planning, material layering, and final processing. Figure 3 displays the complete workflow for manufacturing a component. The manufacturing sequence begins with a computer design that gets transformed into equipment movement paths through strategic planning (Bekker & Verlinden, 2018). This stage requires creating a digital three-dimensional model using design software or capturing physical objects through techniques like 3D scanning, then storing the model in a recognized file type (commonly. stl format). Specialized slicing programs divide the 3D model into buildable horizontal sections of appropriate thickness (Appendix 1: Steps involved in a WAAM of a selected part). Software tools (like 3D Ultimaker CURA) determine the ideal processing path and establish optimal settings for material application, including wire feed speed, tool movement rate, electrical current, protective gas flow, layering approach, and thermal energy input (Singh & Khanna, 2021).

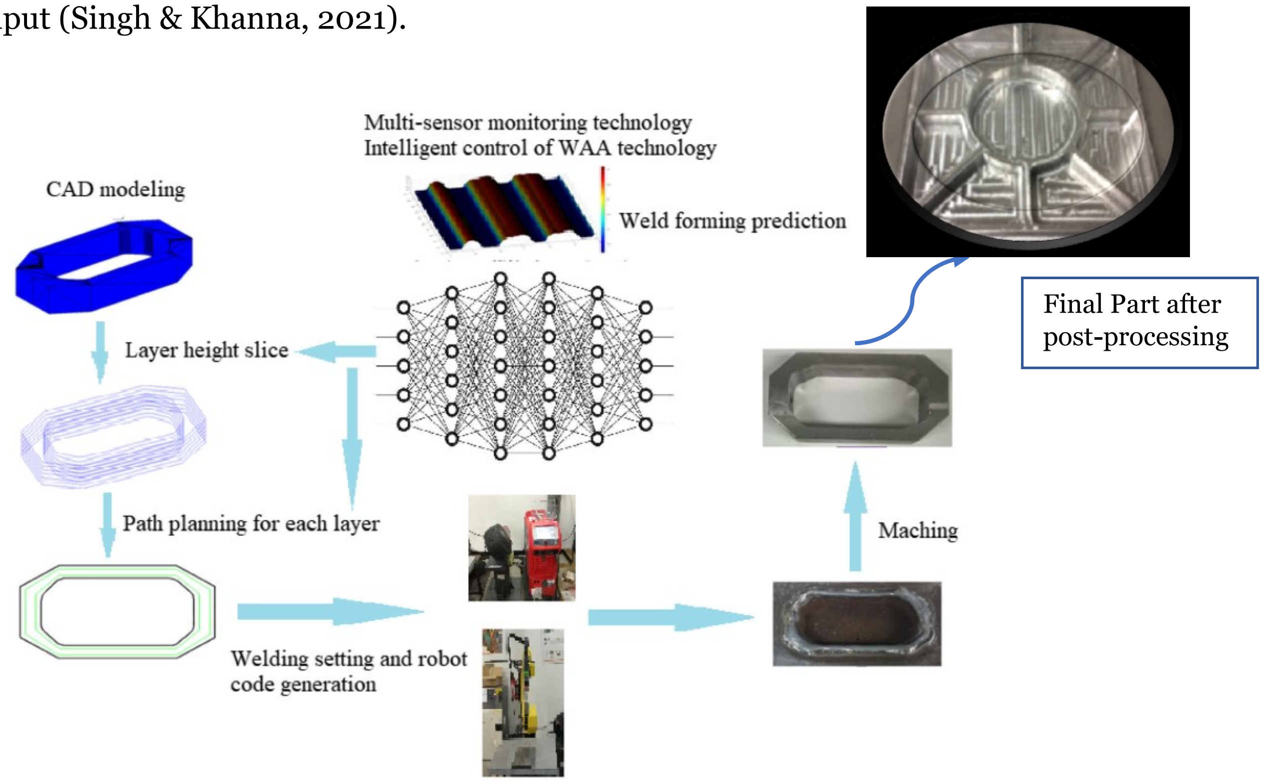

Figure 3. Key process steps in fabricating metal parts with the WAAM process (J. Liu et al., n.d.)

Further, a typical WAAM processing chain can be decomposed into five stages (Figure 4): (1) pre-processing, (2) equipment setup, (3) metal deposition by WAAM, (4) machining and (5) post-processing (Dias et al., 2022). Description can be found in Appendix 2: Explanation of WAAM processing steps.

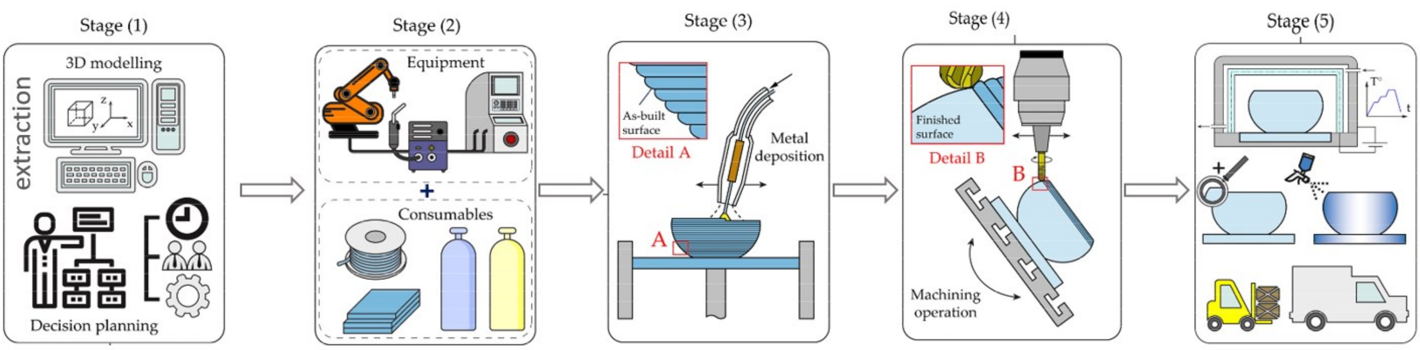

Figure 4. Flow map of a typical WAAM processing chain composed by five main stages (Dias et al., 2022)

2.2. Sustainability in AM and WAAM

Many studies have examined how additive manufacturing (AM) compares to conventional forming and cutting processes. Research findings generally indicate that AM offers better environmental and social benefits because it requires fewer materials during production, leading to reduced manufacturing impacts (Ehmsen et al., 2023).

Wire arc additive manufacturing has emerged as an effective production method for different engineering metals including titanium, aluminum, nickel-based alloys, and various steels (Wu et al., 2018). When measured against conventional machining approaches, WAAM systems can cut production time by 40-60% while reducing finishing operations by 15-20%, though results vary with part dimensions (Wu et al., 2018). Recent advances demonstrate impressive material efficiency - aircraft landing gear components manufactured through WAAM require approximately 78% less raw material compared to traditional machining methods (Ding et al., 2015). The industrial sector has shown growing interest in wire arc additive manufacturing technology because it enables production of large-scale metal parts while offering rapid build rates, affordable equipment costs, excellent material efficiency, and positive environmental characteristics (Wu et al., 2018).

2.3. Life Cycle Assessment (LCA)

According to the European Standard EN ISO 14044 from 2006, covering environmental management and life cycle assessment guidelines, LCA represents a systematic method for evaluating environmental effects and potential environmental impacts throughout a product's lifecycle (from raw material acquisition through production, use, end-of-life treatment, recycling and final disposal (cradle-to-grave)) (EN ISO 14044, 2006; Mitchell, 2017).

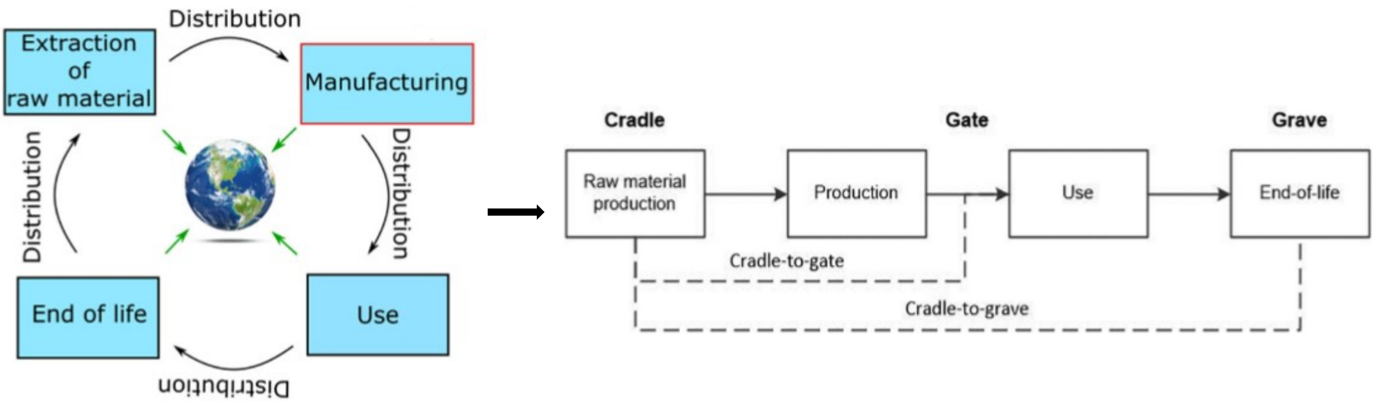

Figure 5. A product life cycle (Kokare, Godina, et al., 2023; Yosofi et al., 2019)

Ecological effects encompass those resulting from releases to the environment and resource utilization, along with other activities (such as land occupation) linked to product delivery that happen during material extraction, substance production, item manufacturing, usage periods, and product end-of-life management (collection/separation, reuse, recycling, waste treatment) (Rebitzer et al., 2004). Such releases and resource usage lead to various consequences including global warming, upper atmosphere ozone reduction, ground-level ozone formation, nutrient enrichment, acid formation, resource depletion, water consumption, land occupation, and sound pollution etc.

Experts and scientists across multiple fields apply Life Cycle Assessment (LCA) to quantify measures of the previously mentioned ecological effects (Rebitzer et al., 2004). LCA specialists record releases and resource usage, plus other environmental interactions throughout each relevant stage in a product's lifespan, spanning "cradle to grave" covering raw material gathering, energy procurement, substance creation, production processes, application, recovery, final disposal, etc. (see Figure 5).

Following the collection, organization, and initial examination of all environmental interactions (releases, resource usage, etc.), termed the Life Cycle Inventory (LCI), specialists typically need to calculate and analyze indicators of potential consequences linked to such interactions with the natural world. This process becomes Life Cycle Impact Assessment (LCIA) (Rebitzer et al., 2004).

Global and developing standards within the ISO 14000 family generally provide an accepted structure for LCA methodology. The international LCA standard applied in this research is ISO 14044: 2006(E) (EN ISO 14044, 2006). Based on the ISO 14044:2006 LCA guidelines, four stages comprise an LCA investigation (see Appendix 4: Definition of LCA phases (from ISO 14044:2006) for explanations).

a) The goal and scope definition phase.
b) The inventory analysis phase.
c) The impact assessment phase.
d) The interpretation phase.

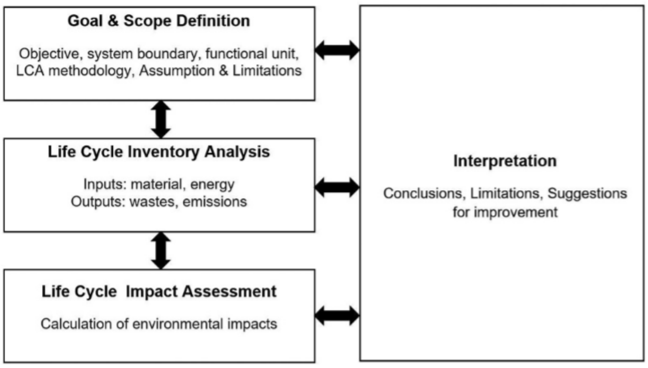

Figure 6. The 4 Phases of an environmental LCA based on ISO 14044:2006

2.3.1. Life Cycle Assessment of Additive Manufacturing (AM) Processes

Research by Kokare, Godina, et al. (2023) indicates that earlier investigations examining AM environmental performance concentrated heavily on power usage while overlooking other resource inputs and elements influencing AM sustainability. Z. Y. Liu et al. (2018) conducted an extensive examination of energy usage in metal AM methods across various operational levels (equipment and process levels) and different operating states (inactive, standby, and active modes). Garcia et al. support this observation, noting that power consumption represented the primary focus in environmental studies of AM, appearing in 87% of reviewed publications.

Current research clearly demonstrates that energy usage in AM methods has attracted more attention than other inventory elements like raw materials, protective gases, material losses, support components, and materials eliminated during finishing operations of AM products. This highlights the need for thorough collection of diverse life cycle inventory (LCI) information across AM methods under varying operational conditions (Kokare, Godina, et al., 2023).

Furthermore, comparing environmental consequences of AM and conventional manufacturing methods is essential to identify the most environmentally sound approaches for sustainable production of specific products (Serres et al., 2011). Regarding LCI information sources and methodologies used, the EcoInvent database serves as the primary resource for life cycle inventory data. Other significant databases include CES and Gabi. ReCiPe represents the predominant impact evaluation approach (Kokare, Godina, et al., 2023).

As outlined in section 2.3, life cycle inventory plays a vital role in documenting inputs and outputs linked to each phase in a product's lifecycle. A significant challenge in achieving precise and thorough life cycle evaluations across additive manufacturing and other production methods like thermo-stamping involves insufficient detailed inventory information. Lacoma et al. (2023) recommended conducting complete manufacturing process descriptions to establish system boundaries for study. The production process gets broken down into individual unit operations representing each production step. Connected to this description, material and energy consumption and waste balances are developed for each unit operation (Kellens et al., 2012; Lacoma et al., 2023).

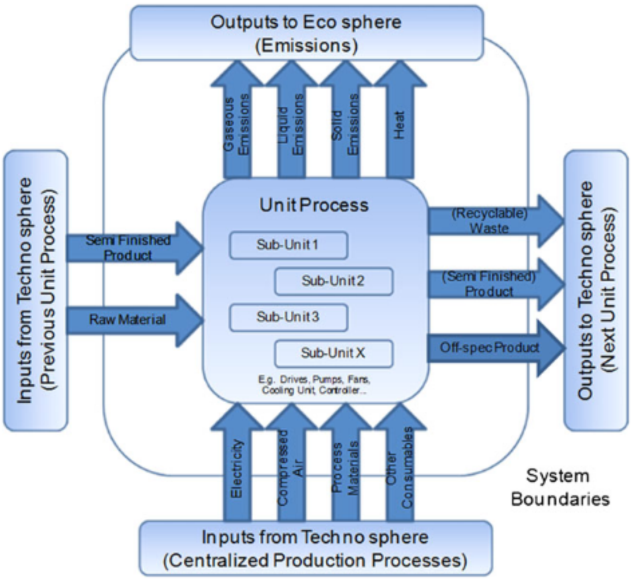

Figure 7. Unit Process LCA Methodology by Kellens et al 2018

2.3.2. LCA of WAAM

This subsection will provide a comprehensive overview of advancements related to implementing LCA methodology within WAAM applications.

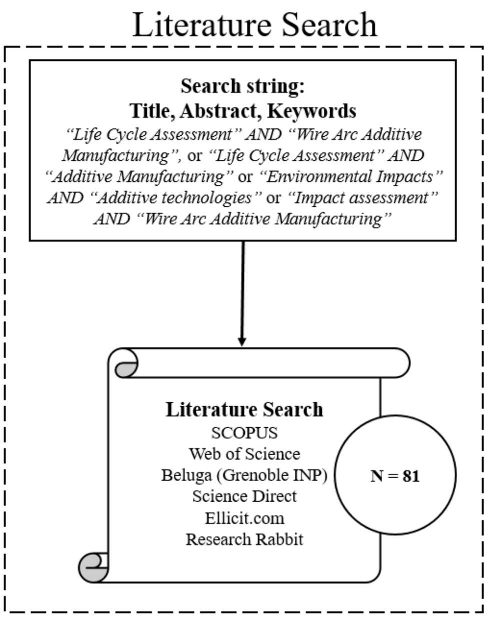

Figure 8. Literature sources used in the state-of-the-art survey

In summary, some researchers reported a material saving of 53% relative to conventional hot-rolling, while others note savings between 40% and 70% when WAAM is compared with CNC milling. Four studies quantified lower CO_2 emissions for WAAM, with values 7% lower for carbon steel and 24% lower for stainless steel than those observed in traditional processes. Increased deposition rates have been linked in one study to a 25% reduction in production time and a greater than 30% decrease in climate change impact. Shielding gas is identified in two studies as a significant contributor to overall environmental impact. The following studies, among others document how choices in material and energy inputs quantitatively shape both the ecosphere outputs and technosphere outputs in the DED-WAAM manufacturing process.

In a 2023 comparative life cycle assessment (LCA), Reis et al. investigated the environmental effects of manufacturing three unique metal components: a gear, a cylinder, and an S-shaped part. Their research compared two production methods: wire arc additive manufacturing (WAAM) and traditional subtractive CNC milling. To measure the environmental footprints of both techniques, the researchers used the SimaPro 9.2 software, adhering to the ISO 14044:2006 standard. They also applied the ReCiPe 2016 method, specifically focusing on its mid-point indicators. The study's key findings revealed that the WAAM process resulted in significant material savings; between 40% and 70%; and a corresponding environmental impact reduction of 12% to 47% compared to the subtractive method.

The (Reis et al., 2023) study's scope was limited by the unavailability of certain equipment, which prevented the inclusion of the post-processing CNC machining stage. Data for the production phases of ER90 steel wire, along with information on compressed air, lubricating oil, water, and electricity, were sourced from the EcoInvent 3 database.

Ultimately, the WAAM process emerged as the more environmentally sound choice across all geometries examined, achieving an average material reduction of 56% and a 35% decrease in environmental impact compared to CNC milling. A key finding, consistent with prior WAAM LCA research, was that steel billet production was the most significant contributor to the environmental impact in both manufacturing processes.

A cradle-to-gate life cycle assessment conducted by Bekker and Verlinden in 2018 examined a 1 kg stainless steel 308L component. They determined that the production of the initial steel billet alone accounted for almost 78% of the total environmental impact of the final wire arc additive manufacturing (WAAM) part. This finding is consistent with research by Priarone et al. (2020, 2021), who also studied WAAM of steel. Their work showed that the feedstock material is responsible for over two-thirds of the cumulative energy demand (CED) for the entire process. A general trend noted in these studies is that the environmental impact has a direct, linear relationship with the finished product's mass.

Jimi et al. (2019) concluded that the environmental footprint of wire arc additive manufacturing (WAAM) is primarily driven by its material needs, particularly during upstream production phases. Their life cycle assessment (LCA) showed that the manufacturing of raw materials is the largest contributor to both primary energy consumption and greenhouse gas (GHG) emissions. This finding aligns with a recommendation from Ehmsen et al. (2023), who suggested that energy and material flows should be modelled independently of specific parts or machines. This approach is also reflected in the concept of unit process LCA by Kellens et al. (2012). However, it is important to note that this specific modelling method does not account for upstream and downstream processes and cannot estimate environmental impact by integrating characterization models for calculation.

A case study by Dias et al. (2022) explored the economic and environmental potential of WAAM. They developed a process-based cost model to estimate production expenses and used a life cycle assessment with ReCiPe midpoint and endpoint levels to evaluate environmental impact. The study's results showed that WAAM can be both economically viable (leading to a 34% reduction in production costs) and environmentally beneficial in specific industrial applications. The authors created a detailed process chain for WAAM, dividing it into five distinct stages: (1) pre-processing, (2) equipment setup, (3) metal deposition, (4) machining, and (5) post-processing. Consistent with other research, the study considered key inputs such as the wire feedstock (AISI 316L SS), the baseplate (hot-rolled steel), shielding gas, and electricity, with data sourced from the Ecoinvent 3.7 database, which represents global averages. SimaPro 7 software was used for the impact assessment modelling.

Pagone et al. (2022) observed that, given the relatively new nature of WAAM, its environmental impact has been studied only to a limited extent. To address this gap, their study performed a life cycle assessment on using WAAM to repair a steel disk drive. The environmental impact parameters they considered were based on the ANSYS Granta EduPack, which provides a range of typical minimum and maximum values.

The study excluded the use and end-of-life phases of the product life cycle but did include the environmental impact of transportation between the manufacturer and the customer. The results highlighted that WAAM has higher material efficiency compared to conventional, subtractive manufacturing. Furthermore, repairing a component with WAAM significantly reduces its environmental impact by avoiding the need to manufacture an entirely new part.

A study by Catalano et al. (2023) assessed the cradle-to-grave environmental and economic impacts of producing Ti-6Al-4V components using wire arc additive manufacturing (WAAM). They examined how different deposition rates influenced key metrics, including cumulative energy demand (CED), CO_2 emissions, manufacturing time, and costs. All of these factors were normalized to the mass of the final part, which served as the functional unit. The findings indicated that higher deposition rates significantly reduced production times. However, the majority of the environmental impact stemmed from the energy consumption and carbon emissions linked to the material production and pre-manufacturing stages.

Last but not the least, Balidas et al., 2024a noted that environmental impact studies on AM technologies, particularly Wire Arc Additive Manufacturing (WAAM), are still in an early stage of development, limiting their maturity and applicability in industrial contexts. To address this, the authors proposed a five-part methodology for conducting LCAs of WAAM processes. The first part presents a case study describing the technical characteristics of the part; such as geometry, material, and integration constraints; and compares WAAM to alternative processes. The second part introduces standardized process trees to harmonize the representation of life cycle stages, allowing for meaningful synthesis across diverse studies. The third part compiles technical parameters required for WAAM part production, recognizing variability across equipment. The fourth part develops detailed life cycle inventories (LCIs) organized by input type, process stage, and manufacturing method, with specific energy consumption (SEC) calculations aiding quantification. Finally, the fifth part focuses on comparing environmental impacts based on compiled data, selected indicators, and methodologies. Together, this structured framework enhances consistency and comparability in LCA studies of WAAM and contributes to addressing the methodological gaps in environmental assessments of AM technologies.

2.4. Key Takeaways from the State of the Art

The review of recent academic literature shows a growing focus on using life cycle assessment (LCA) to evaluate the environmental performance of Wire Arc Additive Manufacturing (WAAM). Studies by Ehmsen et al. (2023), Reis et al. (2023), Dias et al. (2022), and Catalano et al. (2023) have all demonstrated WAAM's potential to significantly reduce material waste and lessen environmental burdens when compared to traditional subtractive manufacturing. This potential for environmental impact reduction is also highlighted in more recent work by Balidas & Kerbrat et al. (2024).

A consistent finding across these studies is that the production of raw materials, especially the fabrication of steel billets, is the largest single contributor to the overall life cycle environmental impact. Beyond material sourcing, other factors that contribute to the environmental footprint include the consumption of shielding gas, the specific material chosen, and the electricity required to power the equipment.

Methodologies based on ISO 14044:2006, such as those proposed by Kellens et al., (2012) and Lacoma et al., (2023), emphasize the importance of defining unit processes with quantified input/output flows and functional units to enable process-specific impact modelling. However, despite notable progress, research gaps remain in comprehensive inventory modelling of WAAM-specific equipment, upstream and downstream integration, and the effects of deposition strategies on the life cycle impacts.

3. Research Methodology and Tools

This chapter presents the ISO 14044:2006 LCA methodology following the unit-process tree approach outlined by Kellens et al. (2012) and Lacoma et al. (2023), as detailed in Section 2.3.1. A process tree for the WAAM process, covering preprocessing, deposition, and post-processing will be developed to identify all technosphere and ecosphere inputs and outputs (section 4.2). The data quality of LCI inputs from the EcoInvent database will be assessed using the Weidema pedigree matrix method (Ciroth et al., 2016; Weidema & Wesnæs, 1996; Wernet et al., 2016). Following this, an experimental case involving the WAAM fabrication of a pentagon-shaped 316L stainless steel part is conducted, from which energy, material, and gas consumption data are collected and used to model the part's life cycle using SimaPro V10. The chapter concludes with a discussion of the project's planning and management.

As a guideline to the steps carried out in this work, the flowchart shown in Figure 9 illustrates the project work breakdown.

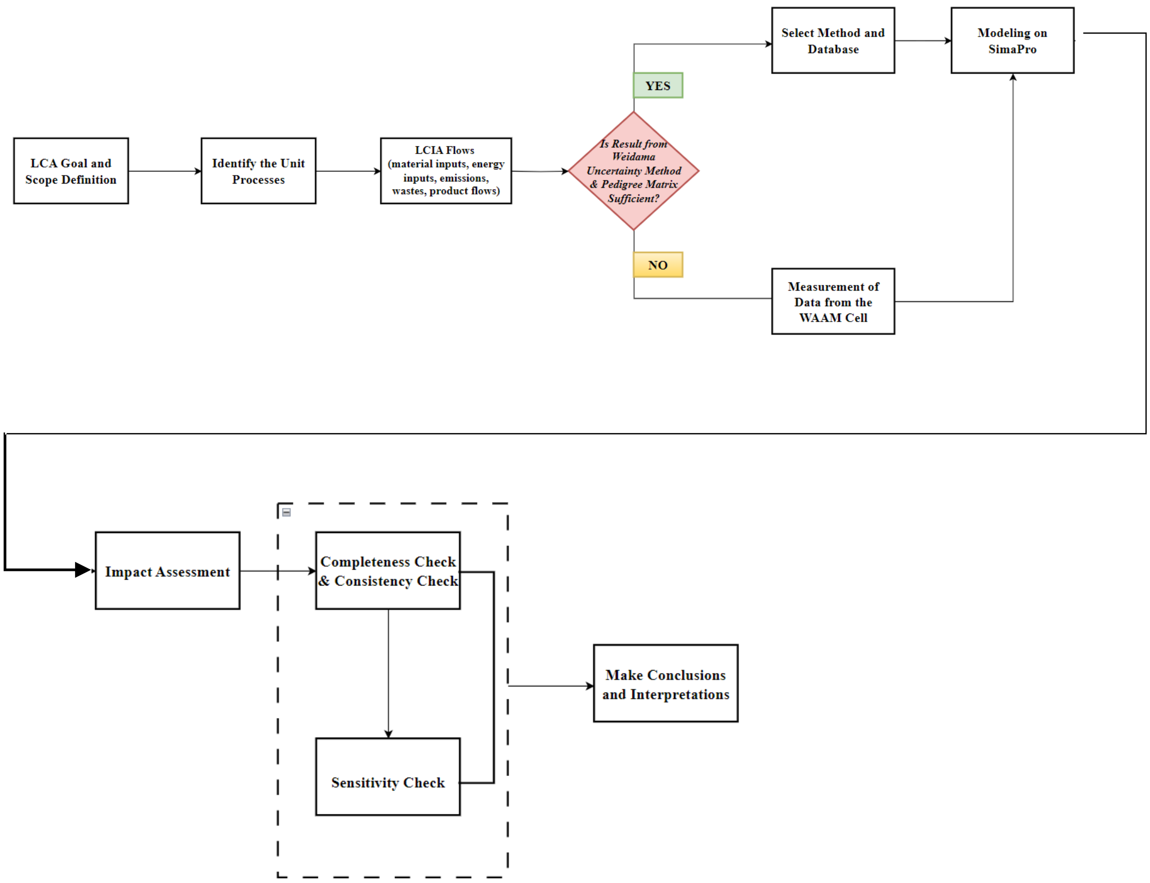

Figure 9. Step by Step flowchart for the LCA of DED-WAAM project

From Figure 9, the circled step is the most crucial one in the context of this work. The goal as stated is to identify the missing data and also assess the reliability of available data which will be key in conducting comprehensive life cycle analysis for the DED-WAAM process. Therefore, the LCIA flows are subjected to an uncertainty assessment using the Pedigree matrix and results displayed in 4.3.

3.1. Unit Process Tree Approach

The manufacturing process, the DED-WAAM process, will be divided into unit processes, each representing a step of production. In the context of our work, these steps/stages are;

a) Pre-planning

b) Pre-processing

c) Deposition

d) Post-processing

A standard flow chart for manufacturing processes has been proposed by Prof. Olivier Kerbrat and Antoine Balidas, both from the *Rennes Institute of Physics at ENS Rennes*, and was therefore applied to build the process tree as recommended by (Kellens et al., 2012; Lacoma et al., 2023).

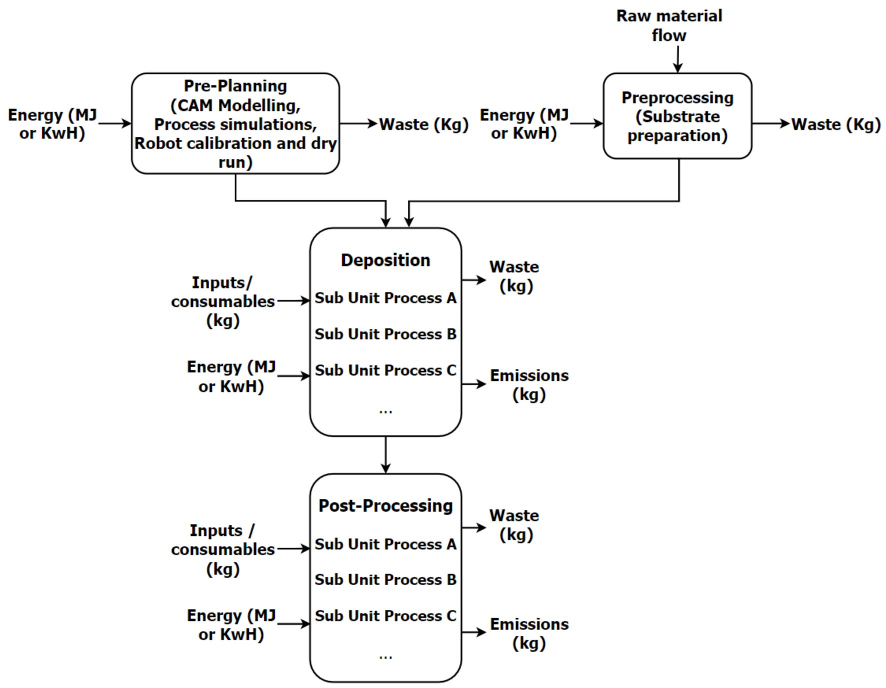

Figure 10. Standard tree model for manufacturing/shaping processes by A.Balidas and O.Kerbrat

3.2. Applied Pedigree Matrix of Uncertainty

EcoInvent database which has been developed by the Swiss Centre for Life Cycle Inventories (Frischknecht & Rebitzer, 2005), applies a method for estimation of default standard deviations for flow data. These standard deviations are then turned into uncertainty factors in a pedigree matrix, comprising of 5 qualitative assessments (Ciroth et al., 2016) as shown below in Figure 11.

Pedigree matrix with 5 data quality indicators

Indicator Score	1	2	3	4	5
Reliability (Source trustworthiness)	Verified data based on measurements. (Verified, measured data)	Verified data partly based on assumptions or non-verified data based on measurements. (Verified estimate)	Non-verified data partly based on assumptions.	Qualified estimate (e.g. by industrial expert).	Non-qualified estimate
Completeness (Representativeness of data)	Representative data from all sites relevant for the market considered, over an adequate period even out normal fluctuations. (Representative & Full) (Data is from all important locations)	Representative data from >50% of the sites relevant for the market considered, over an adequate period to even out normal fluctuations. (Broad coverage) (Data covers more than half of the locations)	Representative data from only some sites (<50%) relevant for the market considered or >50% of sites but from shorter periods. (Medium coverage) (Data comes from fewer than half the important locations)	Representative data from only one site relevant for the market considered or some sites but from shorter periods. (Poor coverage)	Representativeness unknown or data from a small number of sites and from shorter periods. (Incomplete)
Temporal Correlation (Data Age)	Less than three years of difference to year of study. (<3 years)	Less than six years difference. (3-6 years)	Less than 10 years difference. (6-10 years)	Less than 15 years difference. (>10 years)	Age of data unknown or more than 15 years of difference. (Unknown age)
Geographical Correlation (Regional relevance)	Data from area under study. (Exact region)	Average data from larger area in which the area under study is included. (Same continent)	Data from area with similar production conditions. (Similar region)	Data from area with slightly similar production conditions. (Different region)	Data from unknown area or area with very different production conditions. (Unknown origin)
Further technological correlation (Technical relevance)	Data from enterprises, processes and materials under study.	Data from processes and materials under study but from different enterprises	Data from processes and materials under study but from different technology	Data on related processes or materials but same technology	Data on related processes or materials but different technology

Figure 11. Pedigree matrix used with Ecoinvent database (Weidama et al., 1996)

In order to perform the uncertainty factor calculations, the 6 steps indicated by Figure 12 are done in succession to conduct the data reliability scores.

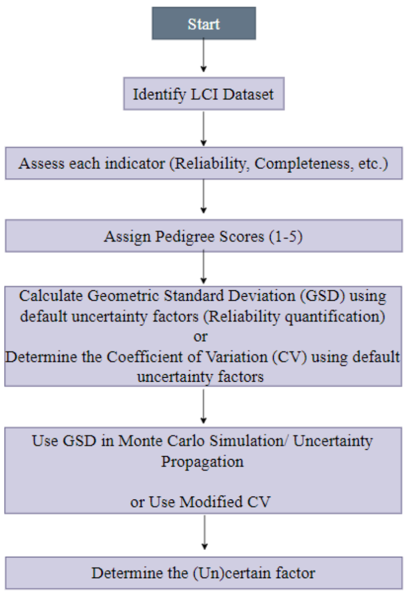

Figure 12. Step by step calculation of uncertainty factors

Once the pedigree scores for each dataset (for example electricity consumption, medium voltage, France) is completed, a Geometric Standard Deviation (GSD) is computed using the formula;

$$U_T = \exp\left(\sqrt{(\ln U_b)^2 + \sum_i (\ln U_i)^2}\right)$$

Where;

UT = Total uncertainty

Ub = Basic uncertainty factor

Ui = Uncertainty factor for each pedigree criterion

The obtained value of UT (also referred to as the SDg95) will determine if a variable can be directly used from Ecoinvent database or a new measured variable is required. This is the test for data reliability. Finally, different levels of uncertainties will be given to each dataset according to Figure 13 below;

SD_{g95} Range	Uncertainty Level
1.00 – 1.10	Very low uncertainty
1.11 – 1.25	Low uncertainty
1.26 – 1.45	Moderate uncertainty
1.46 – 1.75	High uncertainty
1.76 – 2.00	Very high uncertainty
> 2.00	Extremely high uncertainty

Measure

Figure 13. The standard deviation ranges and their interpretation (verdict)

Notice when the value of SDg95 is closer to 1.00, the more reliable that value is considered to be. Conversely, the further away the value gets from 1.00, the more unreliable the value is otherwise interpreted to be. Therefore, within the scope of this work, we recommend that any input or output with an uncertainty factor of 1.50 or higher should be prioritized for direct measurement. This threshold reflects a moderate to high level of uncertainty, indicating that the data may significantly impact the reliability of the LCA results if left unverified.

3.3. Experimentation on the WAAM Cell

3.3.1. Pre-planning

From section 3.1 (*Unit Process Tree Approach*), we described that for the DED-WAAM process, and in general, all manufacturing processes, the first stage involves the pre-planning phase. This phase often includes CAD design, CAM path planning, robot calibration and dry-run simulations. The following parameters as presented in Table 2 were used in depositing approximately 550g 316l SS metal on a 904g SS substrate.

Table 2. Process parameters used in the WAAM experiment

Process parameters	Values
No. of layers	30
Interlayer cooling time	60 s
Path length	14.56 m
Print time	45 min
Deposition height	1.8 mm
Deposition width	4 mm
Base print speed	10 mm/s
Base travel speed	10 mm/s
Preparation time	30 min

The WAAM build parameters summarized for the test part define both the geometric outcome and the process thermodynamics. 30 deposition layers at a height of 1.8mm produced a total build height of 54mm, while the bead geometry (1.8 mm x 4.0 mm) result to a cross-sectional deposition area of 7.2mm2. The print time of 45 min is combined with an interlayer cooling time of 60s, because we have included a thermal management trade-off time. However, electricity consumption during this idle time is still accounted for. Taken together, these parameters illustrate the competing objectives of WAAM; high-deposition rates and material efficiency versus thermal control and post-processing needs. Therefore, further underlining the importance of in-situ monitoring of deposition mass, gas flow and electric power to reduce inventory uncertainty in environmental assessments of WAAM.

3.3.2. Setup

The infrastructure that was used for this experiment include;

1) Robot Kuka KR50 HA
2) Positioner Kuka KP2 HV1100 HW
3) Fronius iWave 400i AC/DC with Additive Pro options

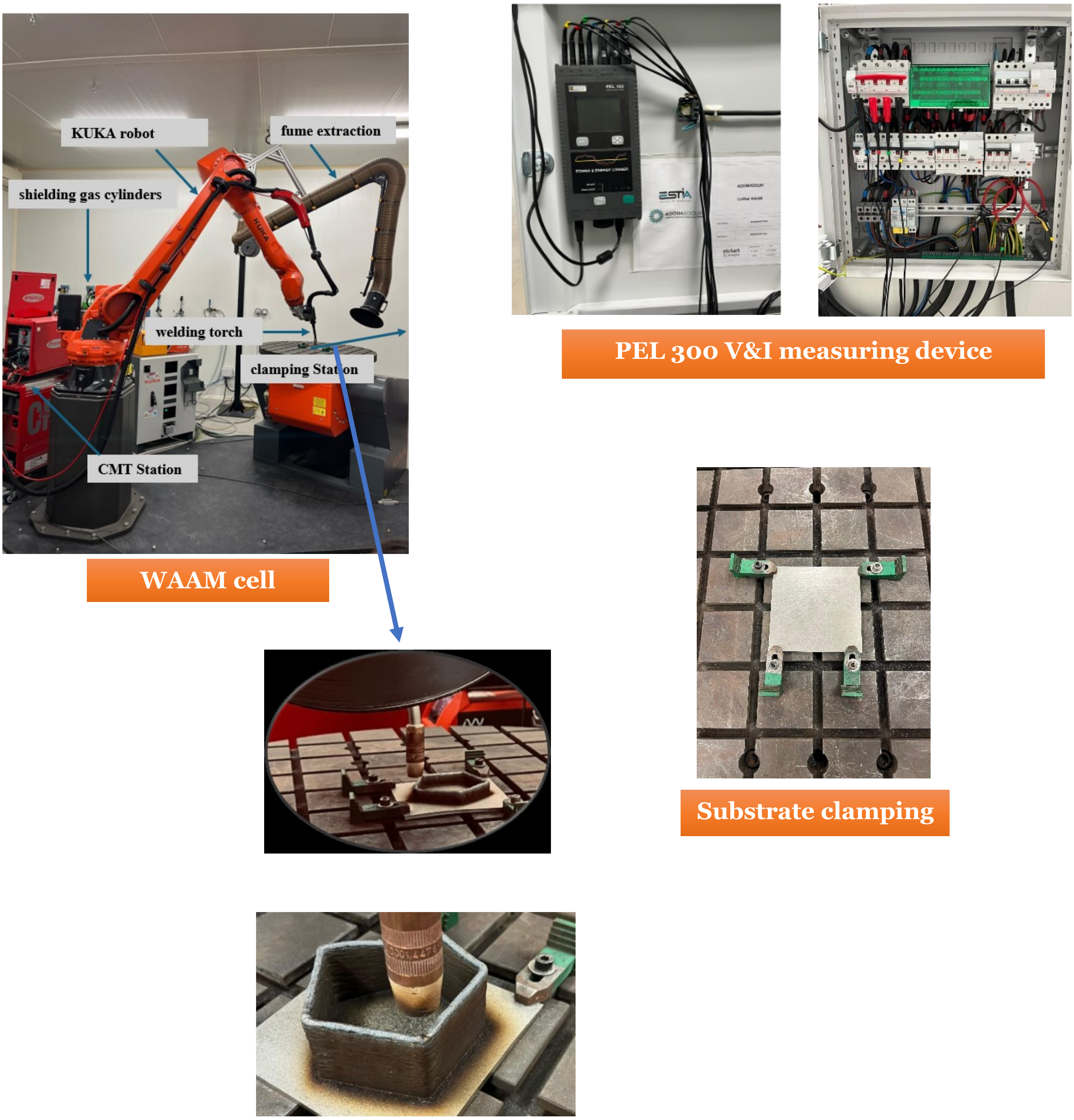

Figure 14. Printed part

3.2. Work Organization and Project Planning

This work was a collective effort of dedication and effective project management that was made possible by a 6-month project timeline, weekly and monthly meetings by the supervision team at ESTIA Institute of Technology and Grenoble INP respectively.

The supervision team at ESTIA Institute of Technology included, Laurent Terrenoir, Laura Laguna Salvadó, and Pierre Michaud from Addimadour Additive Manufacturing Solutions. They provided weekly supervision in the areas of DED-WAAM process, life cycle assessment methodologies, and other administrative procedures. Complementing this team was Olivier Kerbrat, professor from ENS Rennes, an expert in manufacturing processes. His extensive expertise in forming technologies and performance indicators greatly contributed to this work, particularly through his proposal of a unit process tree methodology and the application of uncertainty analysis using the Weidama method (pedigree matrix).

In addition, monthly meetings were held with supervisors from Grenoble INP (France) – Pascal Robert and Sarah Bensrhir and occasional follow-ups from Prof. Mika Salmi of Aalto University, Finland.

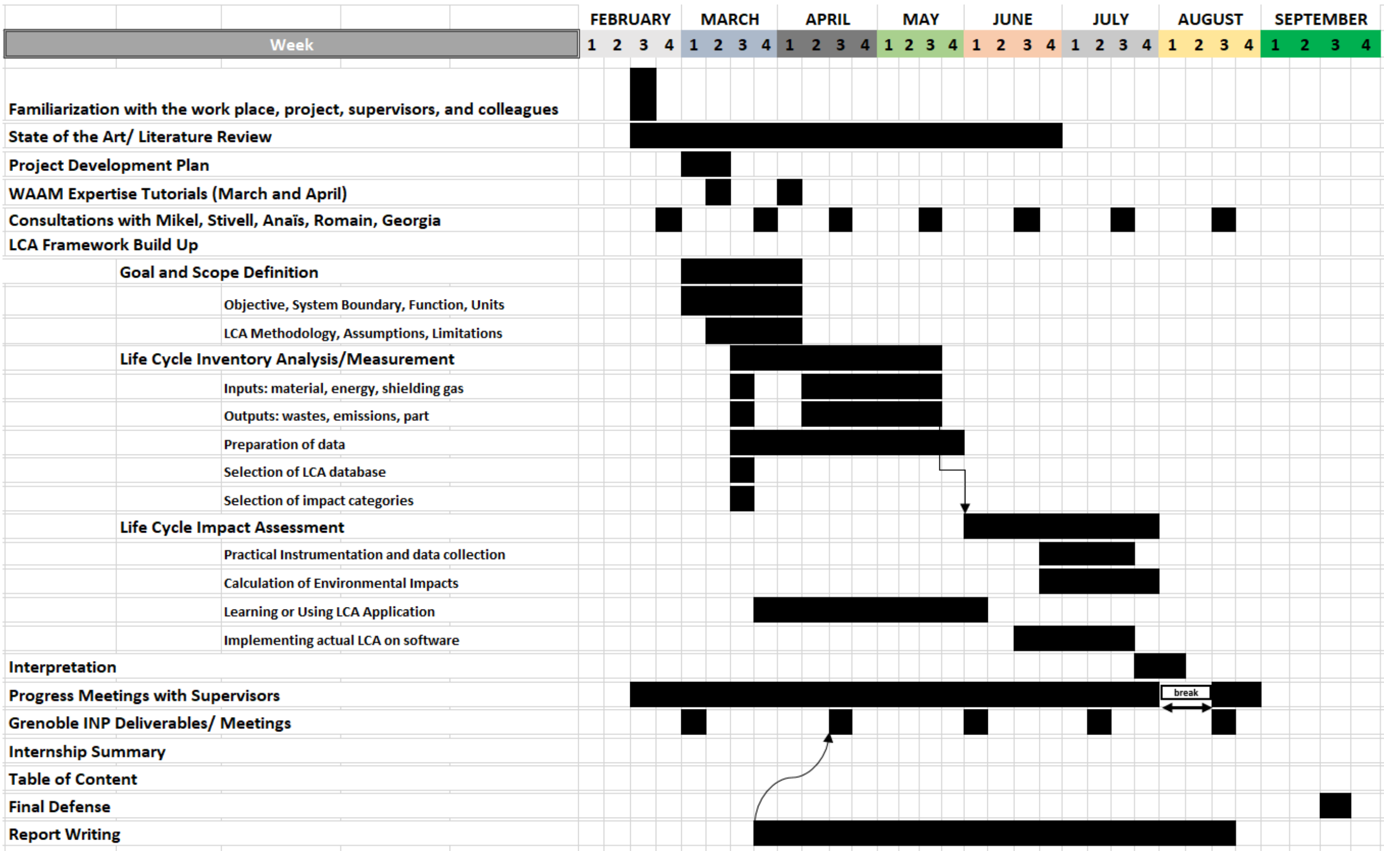

Figure 15. Project Timeline for the thesis work

4. Results and Discussion

Chapter 4 presents the results and discussion obtained from applying the methods, tools, and experiment introduced in the previous chapter. The chapter begins by establishing the LCA goal and scope of the study, then in section 4.2, the DED-WAAM process tree is drawn up with all inputs and outputs from and to ecosphere and technosphere. This is followed by arithmetic calculations of the uncertainty factor for all inputs and outputs alike, as elaborated by the formula in section 3.2. Finally, the outcomes of the life cycle assessment (LCA) of a part manufactured in the Addimadour manufacturing cell will be shown, interpreted in terms of environmental impact categories such as global warming potential (GWP), water consumption and marine eutrophication. The discussion on data quality and reliability as well as LCA results, are explained in relation to existing literature, and also with emphasis on how this work contributes to improving environmental sustainability assessment for the WAAM process.

4.1. LCA goal and scope

A Life Cycle Assessment (LCA) for a part manufactured using the DED-WAAM process is defined. The geometry of the manufactured part is presented, and the experimental setup is described in detail. It is important to acknowledge that not all inputs and outputs recommended for measurement by the uncertainty factor method (as outlined in Section 3.2) could be captured, due to the unavailability of certain measurement instruments and sensors. Nevertheless, energy consumption and material utilization were successfully measured to enable the execution of a first-stage LCA using the SimaPro software.

- Goal of the LCA: The goal of this LCA is to assess the reliability and availability of data required to conduct a comprehensive life cycle assessment for a DED-WAAM process. These data must be applicable to identify key flows that generate environmental impacts (like energy consumption, material usage/waste, emissions) throughout the process.
- Intended application: The intended application is therefore to identify key missing data from inventory analysis and reliability assessment of data that is existing in LCA databases, including measured data from an instrumented WAAM cell.
- Functional Unit: Deposition of a 1 kg of stainless steel part with substrate material using the DED-WAAM process.
- Interested Party: Researchers, LCA practitioners, Industrial engineers, AM Engineers, etc.

4.2. LCA Process Tree

In order to have an accurate overview of the potential impact of WAAM, a detailed inventory analysis of the input (material, consumables, electricity, gas) data and output (heat emissions, waste parts, scrap, etc.,) data is necessary. The unit process tree approach was developed, where the whole WAAM process is broken down into 4 stages;

- Pre-planning – In this stage, the steps involving CAM modelling and process simulations, including robot calibration (dry-run simulation) are defined, complete with their inputs and outputs.
- Pre-processing – During this stage, substrate preparation as carried out within Addimadour's WAAM cell is defined complete with its necessary inputs and output.
- Deposition – The deposition phase is viewed as a unit process which contains three sub-unit processes, i.e., KUKA robot unit, Welding process unit, and Emissions extraction unit.
- Post-processing – The post-processing phase is the last stage of a WAAM process and it involves the following steps in successive order; Heat treatment – CNC Machining (roughing and finishing) – Quality inspection and testing.

Figure 17 is a representation of the process tree flow chart detailing the WAAM process. This flowchart proposes a novel methodology for building the inventory data for WAAM. The arrows from the top and left indicate inputs from technosphere, while the arrow pointing out to the right, represent outputs to ecosphere. Finally, the arrow pointing downwards out of a unit process is an output to technosphere.

The following is a legend explaining flows designated by different colour markings.

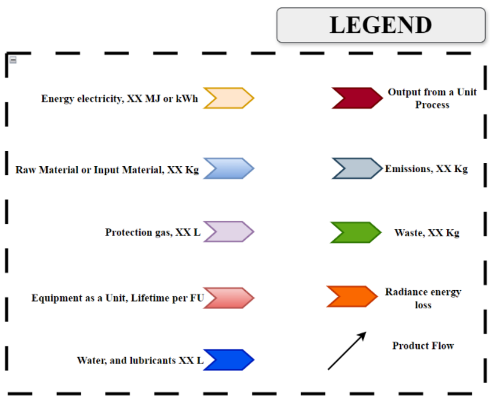

Figure 16. Explanation of flows represented in colour

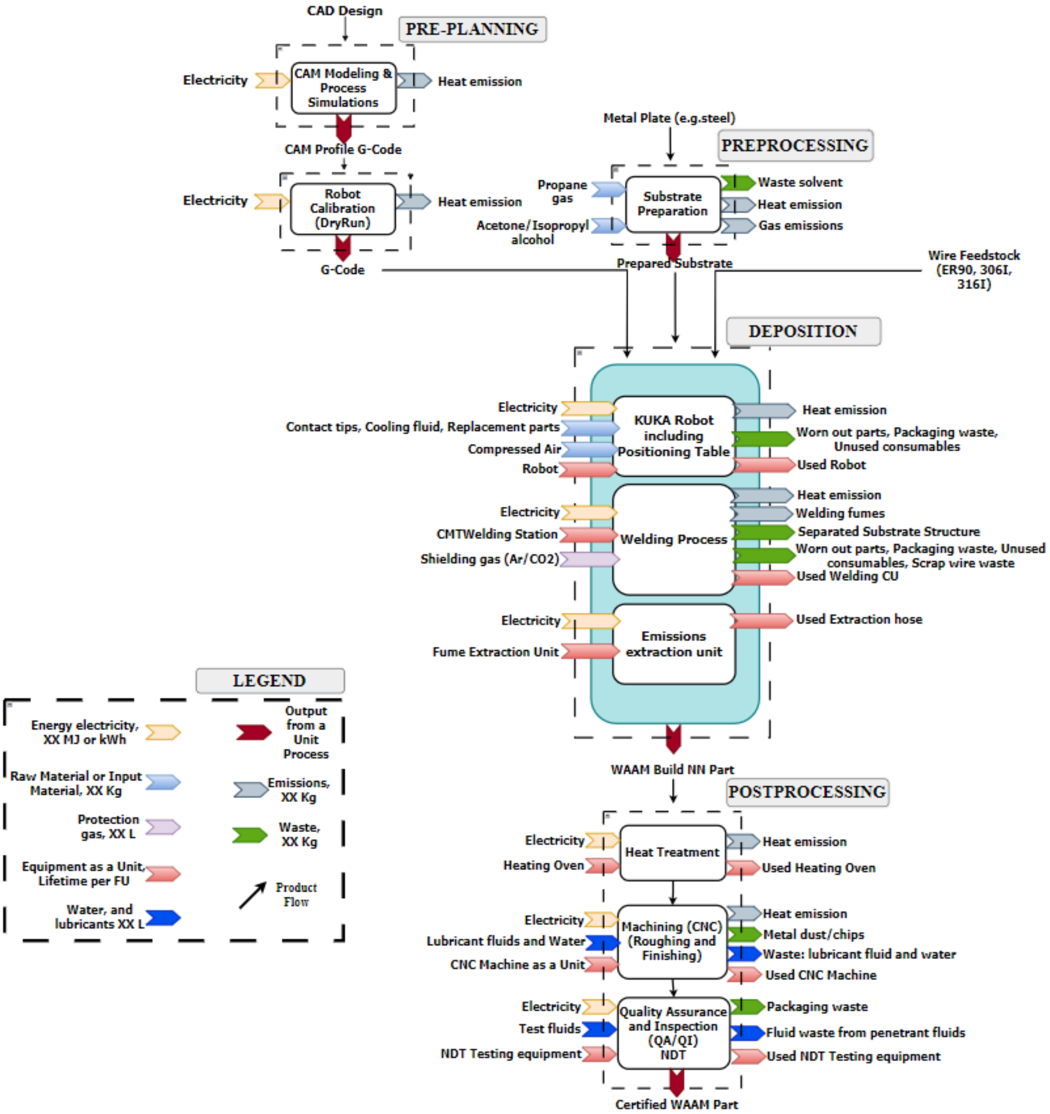

Figure 17. Process Tree for DED-WAAM process

The unit process tree for the DED-WAAM process shown in Figure 17 proposes a framework which decomposes the entire manufacturing route into four structured stages (pre-planning, pre-processing, deposition, and post-processing), explicitly mapping material, energy, and emission flows. This visualization provides a transparent and systematic inventory representation, supporting reliable data acquisition and uncertainty assessment, and constitutes a key methodological contribution of this study.

4.3. Uncertainty Results

From the process tree shown in section 4.2 and Figure 17 the following inputs and outputs (see Figure 18) were parsed through the Pedigree Matrix, also referred to as Weidama Analysis approach, and they were compared with relevant datasets from the ecoinvent 3.0 database.

Input	Best Matching EcoInvent Process
Electrical energy from public grid (France)	Electricity, medium voltage, at grid/FR U
Heat Production, Propane	Heat, from propane, at boiler >100kW, in building
Acetone or Isopropyl Alcohol	Acetone, at plant / 2-propanol, at plant
Wire feedstock (Steel, Ti, Cu, etc)	Steel, low-alloyed, at plant / Titanium, primary, at plant / Copper, cathode
Contact tips (replaced every 2h for a 40h print)	Brass, at plant or Copper product manufacturing
Substrate material; raw material	Steel, low-alloyed, at plant / Aluminium, at plant
Lubricating oil and/or Cooling fluid	Lubricating oil, at plant / Cooling agent (e.g. R134a)
Shielding gas (Ar/CO2)	Argon, liquid, at plant + Carbon dioxide, liquid, at plant
Compressed Air	Compressed air, industrial
CNC Machining (including tools)	Metal working, CNC milling, steel, {GLO}
Water	Tap water, at user / Deionised water, at plant

Output	Best Matching EcoInvent Process
Waste Substrate Structure	Steel scrap, unsorted, at recycling plant {GLO}
Worn out parts	Steel scrap, unsorted / Electronic scrap, for recycling
Heat emissions; emissions to atmosphere	Included in energy generation processes (electricity, heat)
Waste solvent; emissions to water	Solvent, unspecified, waste, hazardous
Packaging waste	Packaging waste, plastic / Packaging waste, cardboard
Scrap wire waste	Metal scrap, steel, low-alloyed, at recycling plant
Metal fumes/spatter; emissions to atm, water, land	Emission to air, heavy metals / metal unspecified
Welding fumes; emissions to atmosphere	Emission to air, PM10 / PM2.5
Metal dust/chips	Metal scrap or emissions to air (fine particles)
Grease and oil waste; emissions to water	Waste oil, hazardous, collected for disposal
Gaseous emissions (Particulate matter, SOx, NOx, Ph)	Emission to air, PM10 / SOx / NOx / Phosphorus
Kilos of material waste in packaging, components	Material-specific waste: plastic, cardboard, metal scrap

Figure 18. Inputs/Outputs compared with best data matches from Ecoinvent

The formula U_T mentioned above was then applied to calculate the geometric standard deviation (GSD) covering 95% of the data. Figure 19 shows how this method was applied to the inputs and outputs. As seen, all 5 qualitative features of data are filled out with a standard deviation defining its reliability.

Input	Reliability	Completeness	Temporal Correlation	Geographical Correlation	Technological Correlation	Basic uncertainty ln(Ub)^2	Total uncertainty factors (UF) Ɛ(ln(UF)^2
Electrical energy from public grid (France)	0.000000	0.000390	0.000000	0.000000	0.000000	0.00238	0.00277
Heat Production, Propane	0.002380	0.000000	0.000000	0.000392	0.000000	0.00238	0.00515
Acetone or Isopropyl Alcohol	0.002380	0.000390	0.000000	0.000099	0.000000	0.00238	0.00525
Wire feedstock (Steel, Ti, Cu, etc); raw material	0.002380	0.000000	0.000000	0.000392	0.033241	0.00238	0.03839
Contact tips (replaced every 2h for a 40h print)	0.033240	0.002381	0.009084	0.000392	0.164400	0.00238	0.21188

Output	Reliability	Completeness	Temporal Correlation	Geographical Correlation	Technological Correlation	Basic uncertainty ln(Ϭb)^2	Total uncertainty factors (UF) Ɛ(ln(UF)^2
Waste Substrate Structure	0.009084	0.009084	0.0000	0.0000	0.033240	0.00238	0.05379
Worn out parts	0.009084	0.000390	0.0000	0.000099	0.033240	0.00238	0.04519
Heat emissions; emissions to atmosphere	0.002380	0.000390	0.0000	0.000099	0.000000	0.00238	0.00525
Waste solvent; emissions to water	0.009084	0.002381	0.0000	0.000392	0.033240	0.16440	0.20950
Packaging waste	0.009084	0.000390	0.0000	0.000099	0.033240	0.00238	0.04519
Scrap wire waste	0.002380	0.000390	0.0000	0.000099	0.033240	0.00238	0.03849
Metal fumes/spatter; emissions to atm, water, land	0.009084	0.000000	0.0000	0.0000	0.000000	0.48045	0.48954

Figure 19. Empirically-based uncertainty factors method applied to inputs/outputs

Finally, the results from the uncertainty analysis are then transformed with an exponential to determine the spread of data on a normal distribution curve. Any input or output with an SDg95 value of 1.50 or more should be measured using instruments such as meters and sensors. The figures (20 and 21) below present the results of uncertainty analysis based on the pedigree matrix and uncertainty factor method.

Input	SDg95	Verdict
Electrical energy from public grid (France)	1.05	Very low uncertainty
Heat Production, Propane	1.07	Very low uncertainty
Acetone or Isopropyl Alcohol	1.08	Very low uncertainty
Wire feedstock (Steel, Ti, Cu, etc); raw material	1.22	Low uncertainty
Contact tips (replaced every 2h for a 40h print)	1.58	High uncertainty
Substrate material; raw material	1.24	Low uncertainty
Lubricating oil and/or Cooling fluid	3.00	Extremely high uncertainty
Shielding gas (Ar/CO2)	1.08	Very low uncertainty
Compressed Air	1.06	Very low uncertainty
CNC Machining (including tools)	3.03	Extremely high uncertainty
Water	1.52	High uncertainty
CMT Welding Station	3.48	Extremely high uncertainty
Heating Oven	3.30	Extremely high uncertainty
Fume extractor	3.30	Extremely high uncertainty
Testing machine/equipment	3.30	Extremely high uncertainty

Figure 20. Uncertainty verdict for the inputs

Output	SDg95	Verdict
Waste Substrate Structure	1.26	Moderate uncertainty
Worn out parts	1.24	Low uncertainty
Heat emissions; emissions to atmosphere	1.08	Very low uncertainty
Waste solvent; emissions to water	1.58	High uncertainty
Packaging waste	1.24	Low uncertainty
Scrap wire waste	1.22	Low uncertainty
Metal fumes/spatter; emissions to atm, water, land	2.01	Extremely high uncertainty
Welding fumes; emissions to atmosphere	2.06	Extremely high uncertainty
Metal dust/chips	2.06	Extremely high uncertainty
Grease and oil waste; emissions to water	1.58	High uncertainty
Gaseous emissions (Particulate matter, SOx, NOx, Ph)	2.00	Very high uncertainty
Used KUKA Robot	3.26	Extremely high uncertainty
Used Welding Unit	3.31	Extremely high uncertainty
Used Extraction hose	3.30	Extremely high uncertainty
Used Heating Oven	3.30	Extremely high uncertainty

Figure 21. Uncertainty verdict for the outputs

This stage led us to conclude that 8 out of the 15 input parameters (53%) in our WAAM cell need to be measured using appropriate measuring instruments. Similarly, 11 out of the 15 output parameters (73%) also require direct

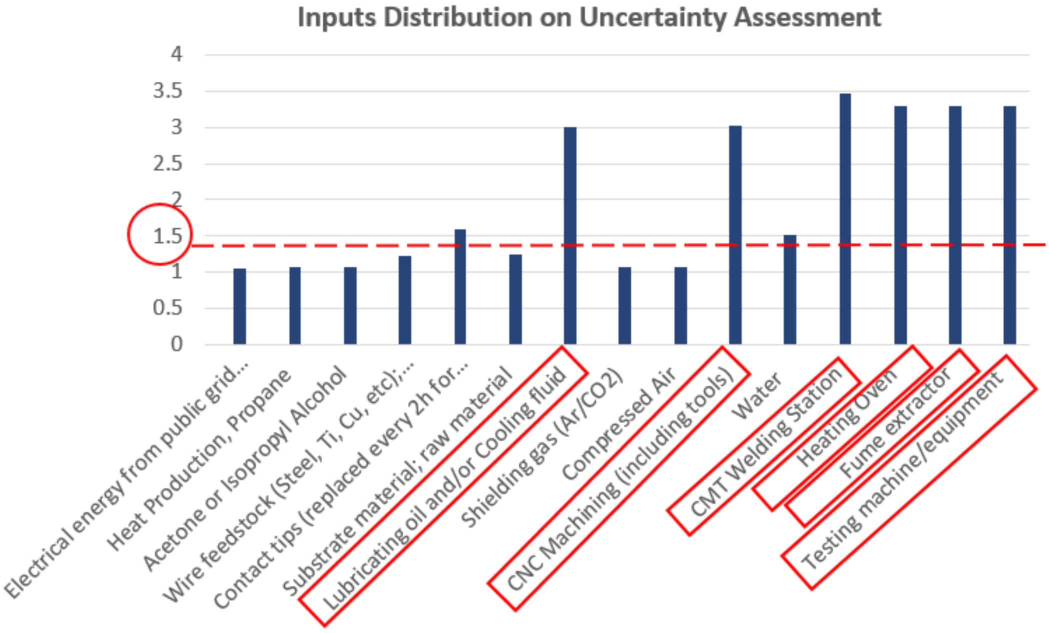

Figure 22. Inputs recommended for measurements in an in-situ WAAM cell.

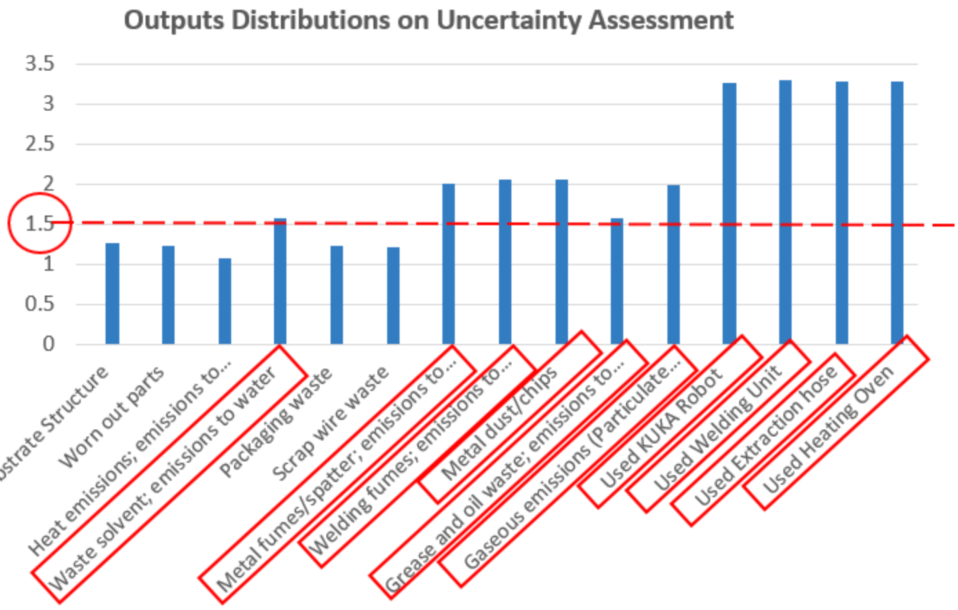

Figure 23. Outputs recommended for measurements in an in-situ WAAM cell.

measurement (see also Appendix 7: Full Tables of the Empirically-Based Uncertainty Factor Approach Method). This insight provides a valuable foundation for future improvements in in-situ data monitoring and process instrumentation.

4.4. Measurements and LCA calculations

4.4.1. Cumulative Energy Demand (Ep)

Electricity was measured using the PEL 300 meter and the following results were obtained;

Robot Energy Consumption
10 layers = 0.08 kWh
29 layers = (29 x 0.08) / 10 = **0.232 kWh**

CMT Energy Consumption
10 layers = 0.328 kWh
29 layers = (29 x 0.328) / 10 = **0.9512 kWh**

Fumes extraction
10 layers = 0.077 kWh
29 layers = (0.077 x 29) / 10 = **0.2233 kWh**

Figure 24. Energy consumed by the robot, CMT, and fumes extraction hose

It is observed that the total energy consumed during the manufacturing process of the 1.45 kg pentagon-shaped stainless steel part was 1.4kWh. However, because we want to find the equivalent power for a 1kg part, these values were normalized to 0.1600 kWh (Robot energy consumption), 0.6567 kWh (CMT energy), and 0.1547 kWh (Fumes extraction consumption).

Important to note is that the 1s measurement power trend for the deposition phase/welding process (see Figure 25a) matched trends that have been reported on literature (see Figure 25b).

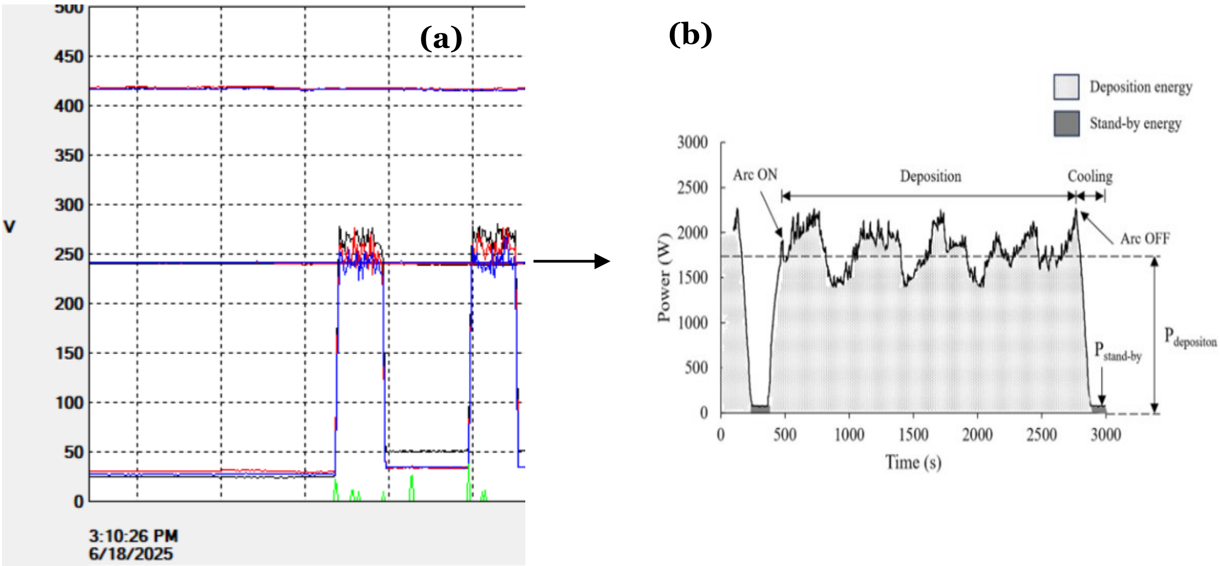

Figure 25. (a) Power trend for the CMT welding station, (b) WAAM process measurement trend from Kokare et al., 2024

4.4.2. Shielding gas consumption

Shielding gas consumption was monitored using Fronius iWave 400i software. The consumption per layer was 10.2 L. Approximately 29 layers were successfully deposited and an equivalent 295.8 L of shielding gas was consumed. The composition for the shielding gas was 88% Argon and 12% CO_2. The following figures (Figure 26 a and b) illustrates how the shielding gas was converted using gas densities into mass and also normalized for the deposition of 1kg part.

- **Total shielding gas usage** (normalized to 1 kg part): **204.0 L**
- **Composition**:
  - Argon = 88% → 0.88 × 204 L = **179.52 L**
  - CO_2 = 12% → 0.12 × 204 L = **24.48 L**
- **Gas Densities at STP**:
  - Argon: **1.784 kg/m³** = **0.001784 kg/L**
  - CO_2: **1.977 kg/m³** = **0.001977 kg/L**

Gas	Volume (L)	Density (kg/L)	Mass (kg)
Argon	179.52	0.001784	**0.3202**
CO_2	24.48	0.001977	**0.0484**
Total	**204.0**		**0.3686**

Figure 26. Shielding gas consumption in (a) litres and densities and (b) mass kg

4.4.3. Material consumption

Material consumption was determined by taking weight measurements of the wire and spool before printing/deposition and then the same weight measurements were repeated after deposition. Taking account of scrap metal wasted, the net deposited metal was calculated, together with the net part weight (substrate + deposited metal).

Part information

- WGIWAM 316L SS + Full Spool = 1102g
- Empty spool = 512g
- Empty spool + remaining wire = 550g
- Substrate material before printing = 904g
- Substrate + printed part (after printing) = 1450g
- Scrap metal and wire = 3.2g

1. Wire Used

- Initial wire mass = 1102 - 512 = 590g
- Remaining wire mass = 550 - 512 = 38g
- Wire used = 590 - 38 = 552g

2. Substrate Used

- 904g

3. Weight of part (deposited + substrate)

- Total mass after printing = 1450g
- Scrap wire/metal = 3.4g

So net part (substrate + deposited metal): 1450g

4. Deposited metal only:

- Deposited metal = 552g (from step 1)
- Net deposition (excluding scrap) = 552 - 3.2 = 548.6g

5. Part weight:

- Substrate + deposited metal = 904g + 548.6 = 1452.6g (very close to the measured 1450g)

Flow	Measured	Normalized (1kg)
Wire	552 g	380.7 g
Substrate	904 g	904 g
Scrap metal	3.2 g	2.3 g

Figure 27. Material consumption and normalized weight consumption

4.4.4. SimaPro LCA Model

The final step to this analysis was the modelling of a life cycle assessment of a 1kg 316l SS part manufactured by the DED-WAAM process. The factors taken into consideration included the material input (wire), substrate part (steel), shielding gas (88% Ar/12% CO_2), and electricity consumption.

The steps followed into developing this LCA can be summarized as follows:

1) First the pre-processing inputs were created from technosphere inputs that exist from the ecoinvent database. These include: electricity, shielding gas composition, and steel wire.

2) A customized welding process was also created as part of a metal welding process and renamed to Wire and Arc Additive Manufacturing. Inputs to this process included the shielding gas, electricity, and wire.

3) Finally, comparison and network diagrams were computed on SimaPro V10 using the ReCiPe method mid-point and end-point characterization.

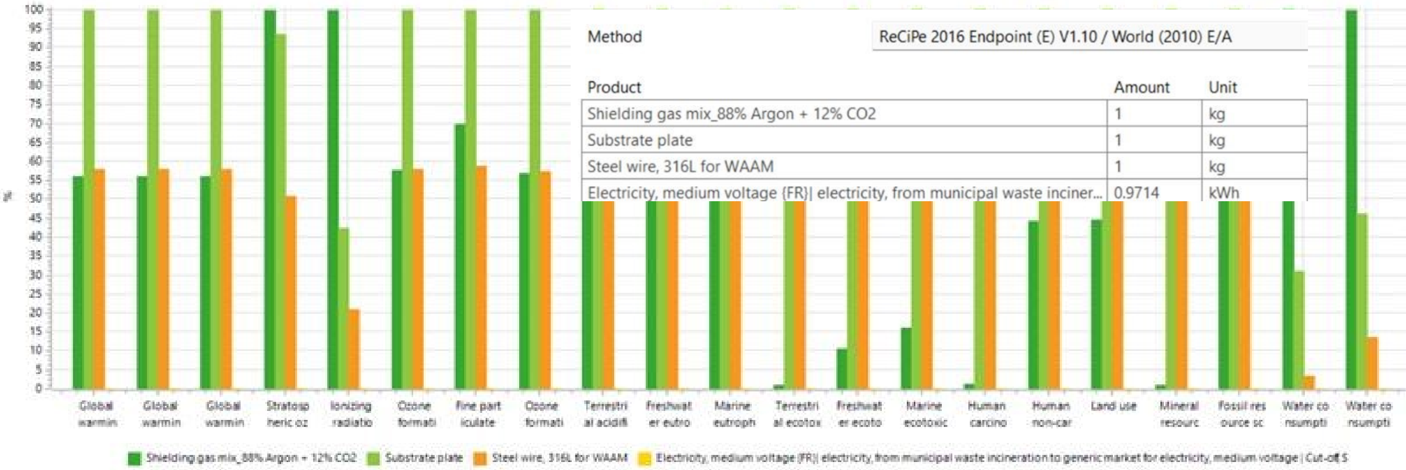

Figure 28. Midpoint impact assessment from the pre-processing inputs

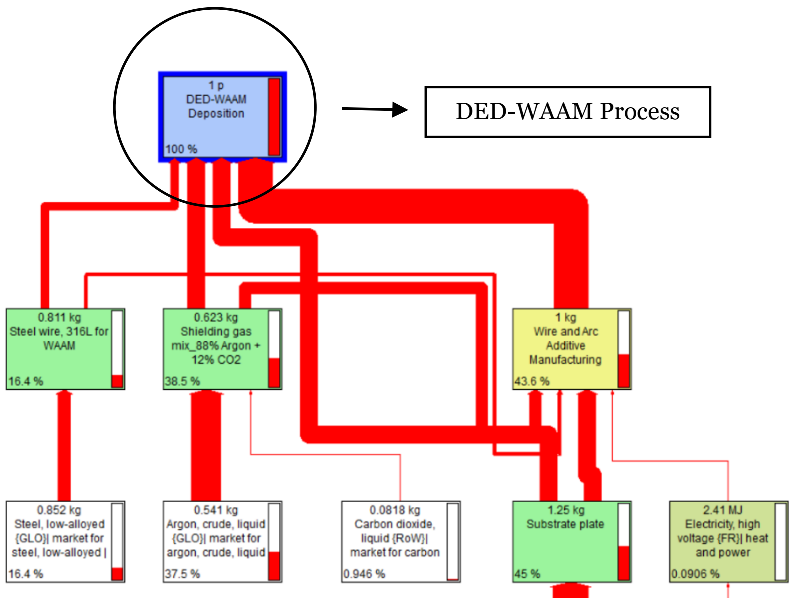

Figure 29. DED-WAAM deposition LCA

The LCIA results show that the substrate plate is the most impactful component in nearly all categories due to mass, energy-intensive processing, and toxic emissions during material extraction and alloying processing. The shielding gas, despite its small mass, contributes highly to stratospheric ozone, depletion, resource scarcity, and water consumption, due to its complex purification and purification processes. The steel wire (feedstock) on the other hand, falls in-between but is still significant in human toxicity, fossil resource use, and acidification.

Table 3. Summary of mid-point impact category results

Impact Category	Top Contributor	Scientific Explanation
Global Warming Potential (GWP)	Substrate Plate	High mass + energy-intensive alloying, smelting, and processing
Stratospheric Ozone Depletion	Shielding Gas	Use of refrigerants or chemicals in gas production with ozone-depleting potential
Ionizing Radiation	Substrate Plate	Nuclear-heavy electricity mix in upstream steel production
Ozone Formation (Human & Terrestrial)	Substrate Plate	Emissions of NO_x and VOCs during melting and energy use
Fine Particulate Matter Formation	Substrate Plate	High-temperature steel processing generates $PM_{2.5}$, PM_{10}
Terrestrial Acidification	Substrate Plate	SO_2 and NO_x emissions from steelmaking and fossil fuels
Eutrophication (Terrestrial, Freshwater)	Substrate Plate	Industrial wastewater, mining runoff, and nutrient discharges
Ecotoxicity (Marine, Terrestrial, etc.)	Substrate Plate	Leaching of Cr, Ni, and other metals from stainless steel production
Human Toxicity (Carcinogenic & Non-C.)	Substrate Plate	Toxic metal emissions (especially Cr VI, Ni) in alloy production
Land Use	Substrate Plate	Raw material extraction and mining of alloying elements
Resource Scarcity (Fossil/Mineral)	Shielding Gas	CO_2 and Argon production are energy-intensive and rely on rare/extracted resources
Water Consumption	Shielding Gas	High cooling and purification water use in gas compression/liquefaction

The environmental impact results observed in this study are consistent with previous findings in the literature on Wire Arc Additive Manufacturing (WAAM). Studies such as Kellens et al., 2012; Lacoma et al., 2023 have emphasized that the substrate material and metal wire significantly dominate the environmental burden across most impact categories, particularly global warming potential (GWP) and resource depletion, due to their energy-intensive production processes.

The high contributions of shielding gas, especially in categories like water consumption and fossil resource scarcity, are also supported by Yang et al. 2017, who noted that gas mixtures (argon-CO_2) used in DED processes contribute to upstream emissions due to gas extraction, purification, and compression processes.

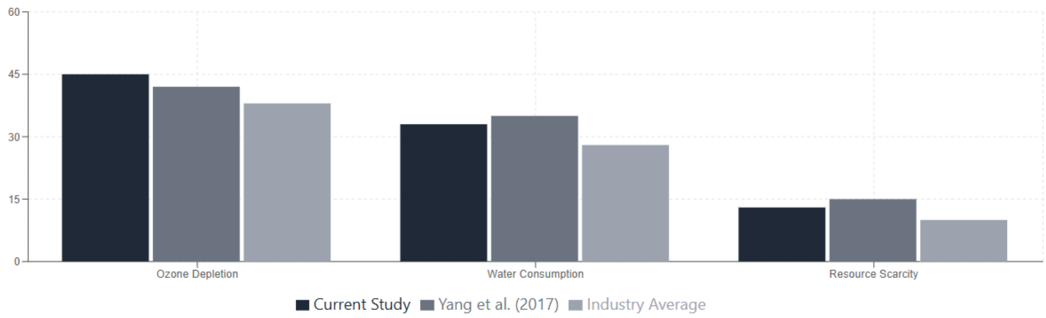

Figure 30. Shielding gas environmental impact (literature validation).

Moreover, the relatively lower impact of electricity in the overall environmental profile aligns with findings by Le Bourhis et al., 2014, which observed that WAAM's electric energy use is lower than that of powder-based AM techniques, due to more efficient deposition rates.

Below is a summary of results obtained from existing literature in comparison to our study;

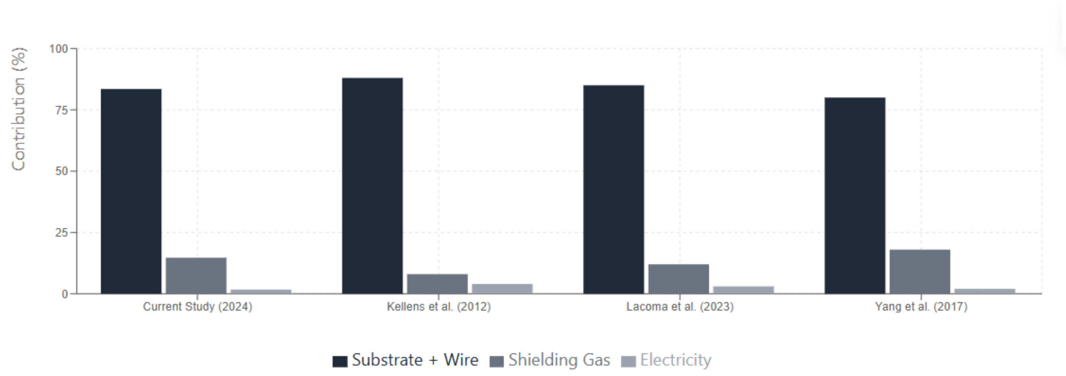

Figure 31. Comparison with existing literature (material vs process contributions).

Comparative analysis shows strong agreement between current finding and established literature. Material contributions consistently dominate (80-88%), with current study at approximately 83.5%.

Finally, with regards to other manufacturing studies, WAAM demonstrates energy efficiency compared to SLM, EBM, and FDM (Bourhis et al., 2014).

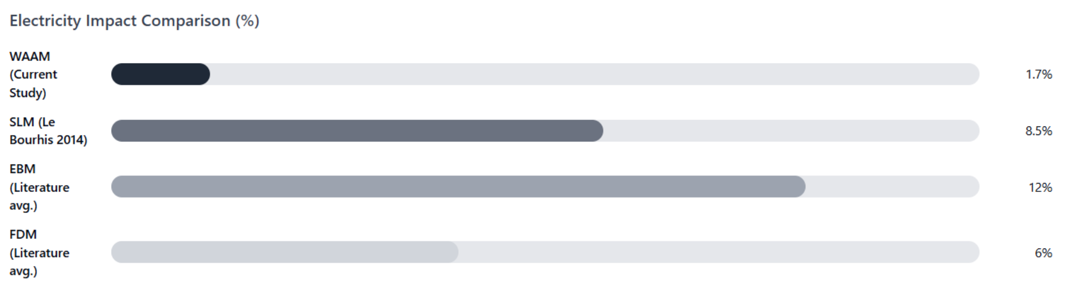

Figure 32. WAAM performance vs other manufacturing processes.

Table 4. Brief summary of literature findings vs current study.

Study	Year	Material Impact (%)	Gas Impact (%)	Electricity (%)	Key Finding
Current Study	2024	83.5	14.7	1.7	High gas impact in ozone depletion (45%)
Kellens et al.	2012	88	8	4	Material dominance in GWP and resource depletion
Lacoma et al.	2023	85	12	3	Confirmed substrate and wire significance
Yang et al.	2017	80	18	2	Emphasized gas upstream emissions
Le Bourhis et al.	2014	92	6	2	WAAM efficiency vs powder-based AM

5. Conclusion

The integration of a process tree modelling approach allowed a clear mapping of all unit processes; pre-processing, deposition, and post-processing, and the respective input/output flows from both the technosphere and ecosphere. By structuring the WAAM system into a detailed process tree, it became possible to identify WAAM flows and compare with existing ones from LCA datasets like ecoinvent.

Furthermore, the uncertainty assessment using the Weidama pedigree matrix further provided a scientific method to assess the reliability and accuracy of datasets from LCA databases. Using this technique, we were able to identify the inputs and outputs that would require measurements in an effort to develop in-situ data monitoring on environmental impacts of the DED-WAAM manufacturing process. As shown in Figures 20 and 21, 53% of the inputs and more than 70% of the outputs will require special monitoring using instrumentation of the WAAM cell. Overall, the combination of the process tree and pedigree-based uncertainty evaluation offers a more rigorous and systematic method for conducting LCAs of emerging metal additive manufacturing techniques such as WAAM.

Finally, the LCA results obtained from SimaPro reaffirm that material inputs, particularly the metal wire and substrate plates are the primary environmental hotspots in WAAM systems. However, the implementation of detailed in-situ sensor integration is expected to reveal whether other, often overlooked, inputs and outputs may also contribute significantly to the overall environmental impact.

5.1. Contribution to knowledge

This thesis contributes to knowledge by advancing the understanding of sustainability assessment in Wire Arc Additive Manufacturing (WAAM) through the integration of Life Cycle Assessment (LCA) with process-level modelling.

First, it introduces a structured process tree modelling framework tailored for WAAM, which systematically maps unit processes; including pre-processing, deposition, and post-processing, together with their respective input and output flows from both the technosphere and ecosphere. This framework offers a more granular and transparent means of capturing environmental exchanges than conventional top-down LCA datasets, which often generalize or omit process-specific details.

Second, the study generates experimental LCA inventory data for DED-WAAM that has been largely absent in existing literature. By quantifying critical process flows such as energy consumption, shielding gas use, material waste, and emissions, the work fills a significant data gap in LCA databases, thereby improving the reliability and accuracy of sustainability evaluations for metal additive manufacturing.

Third, the thesis demonstrates the potential of comparative analysis between WAAM and conventional manufacturing processes, providing evidence of WAAM's advantages in material efficiency and design flexibility, while also highlighting the areas where environmental performance remains uncertain or underexplored. This positions the work as a valuable reference for both academic researchers and industrial practitioners seeking to evaluate trade-offs between emerging and established technologies.

Finally, the research identifies methodological limitations and future directions for LCA in additive manufacturing, particularly the absence of in-situ monitoring and real-time environmental data acquisition. By articulating this gap and proposing pathways toward data-driven monitoring strategies, the thesis lays the groundwork for subsequent research to integrate sensor-based measurements with LCA modelling, enabling more dynamic, accurate, and decision-oriented sustainability assessments.

In sum, the thesis not only extends the body of knowledge in sustainable additive manufacturing but also provides a methodological basis and empirical evidence that can guide future academic inquiry, industrial practice, and policy considerations related to the environmental impacts of advanced manufacturing technologies.

5.2. Challenges and Limitations during the thesis

Despite the valuable contributions of this study, several challenges and limitations were encountered that shape both the scope and interpretation of the findings. First, the availability and quality of data posed a recurring challenge. Reliable process-specific LCA datasets for WAAM and Directed Energy Deposition (DED) were scarce, necessitating reliance on experimental measurements and assumptions that may introduce uncertainty in impact results. The absence of standardized data formats and inconsistencies across existing literature complicated the task of benchmarking WAAM against conventional processes.

Second, the research was constrained by limited in-situ monitoring and measurement capabilities. Key environmental indicators such as real-time gas emissions, thermal radiation losses, and process-induced particulate matter could not be directly measured within the experimental setup. This limited the completeness of the input/output inventory and underscored the need for advanced instrumentation in future work.

Third, process variability and equipment constraints introduced additional uncertainties. WAAM systems are highly sensitive to parameters such as current, voltage, feed rate, and shielding gas flow. Small variations in these parameters can significantly influence energy consumption and material efficiency, yet capturing this variability comprehensively was beyond the scope of this work.

Finally, the study faced time and resource constraints that limited the breadth of comparative analysis with other manufacturing technologies. While the work established a methodological basis and produced indicative results, a more exhaustive industrial-scale validation remains necessary to fully generalize the findings.

These challenges do not undermine the contributions of the thesis but rather highlight important areas for refinement. Acknowledging these limitations provides a foundation for future research to enhance data accuracy, integrate real-time monitoring, and broaden comparative assessments of sustainable additive manufacturing.

6. Recommendations / Future Perspectives

Despite aligning with existing literature, this study also highlights critical gaps in Life Cycle Assessment (LCA) data quality, especially concerning real-time process monitoring. One major limitation encountered was the lack of in-situ measurement of process parameters (e.g., real-time gas emissions, thermal emissions, post-processing material waste, equipment lifetime measurements, etc.), which limited the precision of input/output inventories.

This challenge is not unique; Fera et al. 2020 and Baumers et al. 2017 also identified a general lack of high-resolution, process-specific LCI datasets for metal additive manufacturing**.** Incorporating in-situ data acquisition systems, such as thermal imaging, particulate emissions trackers, current-voltage sensors, and deposition tracking tools, could greatly enhance the fidelity of environmental modelling by reducing uncertainty in process energy and material use. Moreover, AI-assisted monitoring and digital twins have been mentioned in literature to offer promising directions to close these data gaps. Future research should thus prioritize integrating sensor systems into DED-WAAM cells to generate high-fidelity environmental datasets, especially where large-scale parts are built over long durations.

To address these limitations, future research should prioritize the deployment of sensors and/or monitoring devices within the WAAM cell. Specific in-situ measurements that can be implemented include:

- Shielding gas consumption: using mass flow meters or thermal mass flow controllers to log real-time argon/CO2 usage, instead of relying on the Fronius software which was difficult to verify as 100% reliable.
- Welding fumes composition: employing exhaust gas analysers to quantify emissions and particulate matter (e.g., NO, ozone precursors, and metal fumes) (Deepak et al., 2023).
- Heat or thermal emissions: using infrared (IR) thermal cameras or pyrometers to monitor heat dissipation and energy loss (Richter et al., 2021).

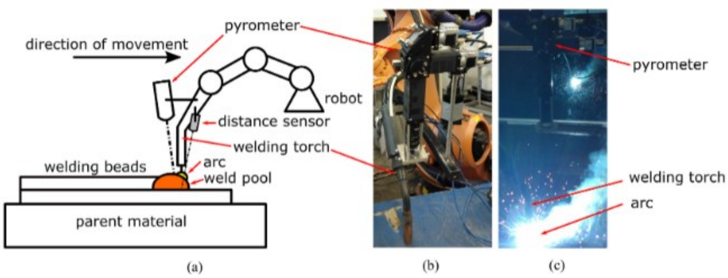

Figure 33. Example of thermal measurements using and IR pyrometer (Richter et al., 2021)

- Current and voltage monitoring: installing inline voltage/current sensors for all individual equipment within the cell will enhance tracking of energy consumption during deposition.
- Machine lifetime data: Recording usage hours of tools such as the welding torch, welding unit, robot arm and fumes extraction funnel will improve life cycle based modelling, allowing a more accurate cradle-grave or cradle-grave life cycle assessment of the WAAM process.

Implementing these suggestions among others, will not only enable a more accurate inventory modelling, but also reduce uncertainty in key impact categories. Other researchers have also proposed the use of advanced AI-assisted monitoring and digital twin frameworks promising opportunities for automated data collection (Ping Chen et al., 2025).

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Appendix 1: Steps involved in a WAAM of a selected part

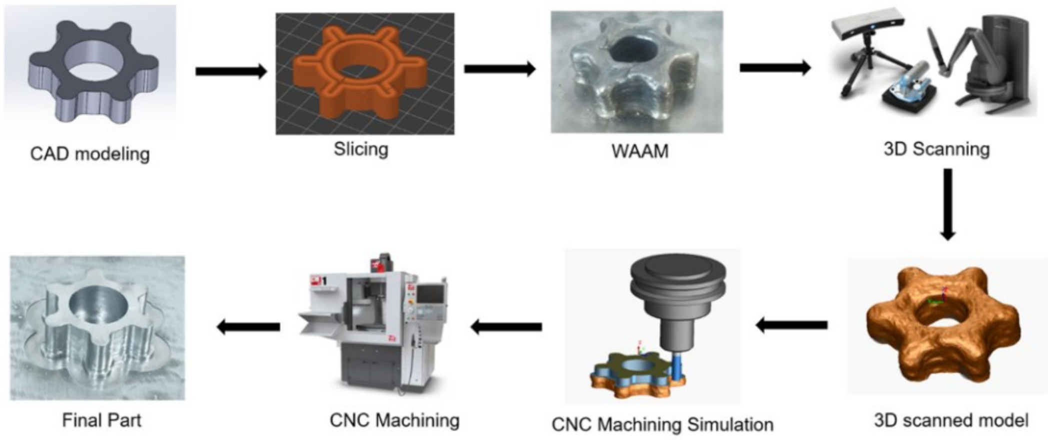


Figure 34. Steps in WAAM of a selected part (Singh & Khanna, 2021)

Appendix 2: Explanation of WAAM processing steps

WAAM Process Chain

The process for Wire Arc Additive Manufacturing (WAAM) can be broken down into five distinct stages, though the first and last are common to many other manufacturing methods.

Pre-processing Stage

This initial stage involves all the planning and modeling tasks. It includes creating a 3D model of the part, selecting appropriate processing parameters, and designing the deposition strategy and path planning for the next steps.

Equipment Setup Stage

This on-site stage prepares the WAAM cell for operation. Key tasks include setting up the machinery, securing the baseplate with clamps, and installing consumables like the wire feedstock and shielding gas.

Metal Deposition Stage

This is the core of the WAAM process, where the part is built up layer by layer into a near-net shape. This is done based on the strategies and parameters established in the previous stages.

Machining Stage

During this stage, the near-net-shape part is refined to meet the required geometric precision, dimensional tolerances, and surface quality. This may also include cutting tasks, such as separating the final part from the baseplate.

Post-processing Stage

This final stage encompasses all finishing operations. These can include heat treatments, polishing, quality inspection, painting, and transportation.

While the pre-processing and post-processing stages are also standard in conventional manufacturing, such as casting or machining from a solid, stages two, three, and four are the most unique to additive manufacturing technologies like WAAM.

Appendix 3: The structure and components of LCA

The figure below shows a schematic representation of a generic life cycle of a product (the full arrows represent material and energy flows, while the dashed arrows represent information flows).

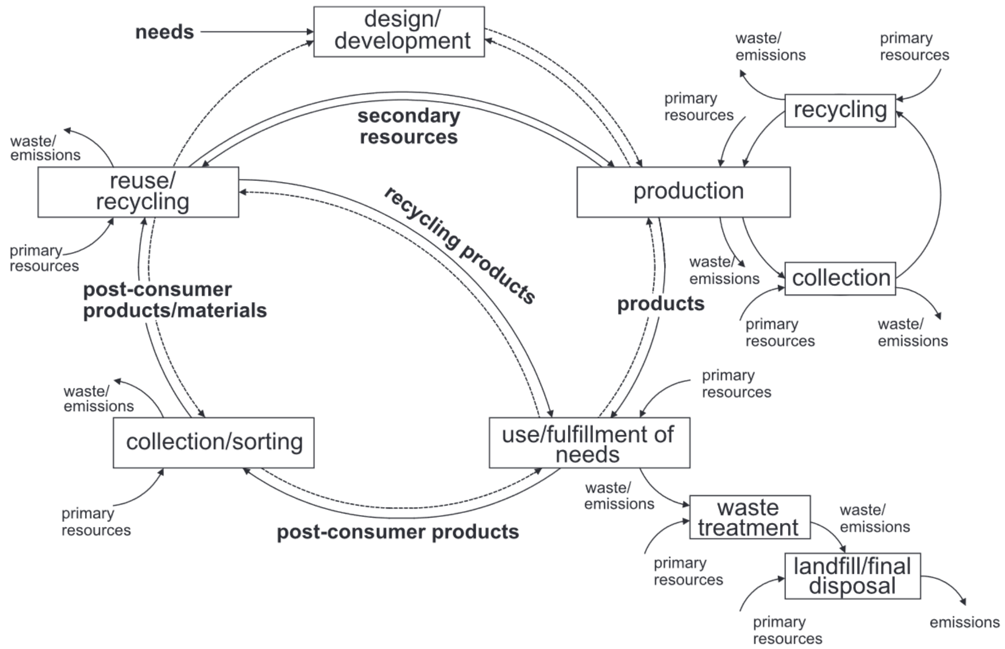


Figure 35. Structure and components of LCA (Rebitzer et al., 2024)

Similarly, below we find a typical illustration of the life cycle of a product, in this case, an automobile.

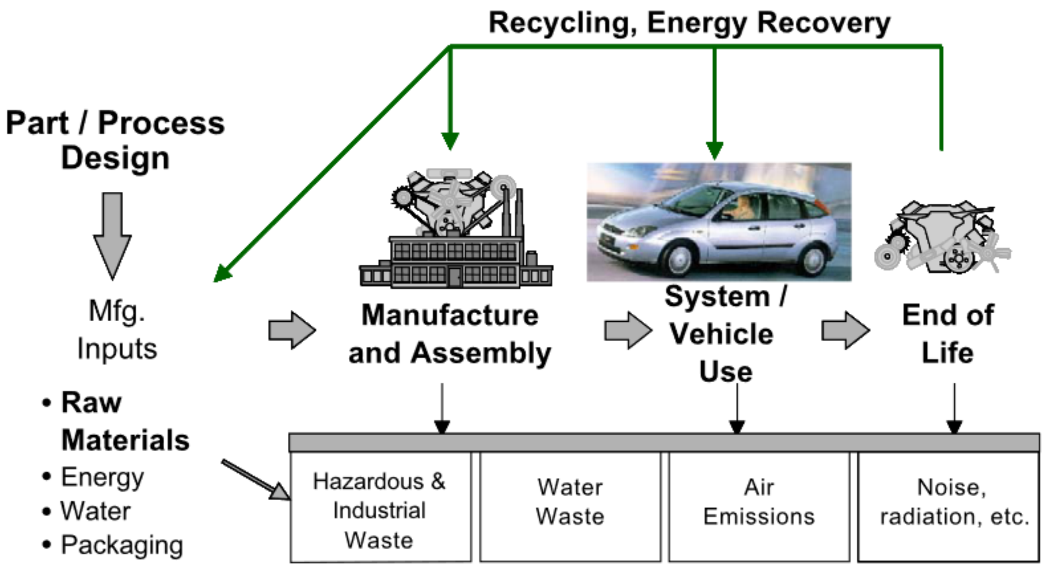


Figure 36. Illustration of the LCA process of an automotive (Rebitzer et al., 2004)

Appendix 4: Definition of LCA phases (from ISO 14044:2006)

Phases of Life Cycle Assessment (LCA)

The depth of a Life Cycle Assessment (LCA) varies depending on its intended purpose and the subject being studied. The goal and scope of the assessment, including its system boundaries and level of detail, are defined at the outset to guide the entire process.

Life Cycle Inventory (LCI) Analysis

The second phase of an LCA is the Life Cycle Inventory (LCI) analysis. This involves gathering all necessary input and output data for the product system under review. It's an essential data collection step designed to fulfill the goals of the study.

Life Cycle Impact Assessment (LCIA)

The third phase is the Life Cycle Impact Assessment (LCIA). Its purpose is to provide context to the LCI results, helping to interpret their environmental significance.

Life Cycle Interpretation

The final phase is Life Cycle Interpretation. In this step, the findings from either the LCI or LCIA (or both) are summarized and evaluated. This provides a foundation for conclusions, recommendations, and informed decision-making, aligning with the initial goal and scope.

In some cases, a study's objective can be met by performing only the inventory analysis and interpretation. This is known as a Life Cycle Inventory (LCI) study, which differs from a full LCA by excluding the LCIA phase. It's crucial not to confuse an LCI study with the LCI phase, which is a component of a complete LCA. International standards recognize both full LCA studies and the more limited LCI studies.

Appendix 5: Basic Uncertainty factors (U_b)

Uncertainty Factor UF approach			
Input/ Output group	c	p	a
demand of:			
thermal energy, electricity, semi-finished products, working material,	1.05	1.05	1.05
waste treatment services.	-	-	-
Transport services (tkm)	2.00	2.00	2.00
Infrastructure	3.00	3.00	3.00
resources:			
Primary energy carriers, metals, salts	1.05	1.05	1.05
Land use, occupation	1.50	1.50	1.50
Land use, transformation	2.00	2.00	2.00
pollutants emitted to water:			
BOD, COD, DOC, TOC, Inorganic compounds (NH4, PO4, NO3, Cl, Na, etc)	-	1.50	-
Individual hydrocarbons, PAH	-	3.00	-
Heavy metals	-	5.00	1.80
Pesticides	-	-	1.50
NO3, PO4	-	-	1.50
Pollutants emitted to air:			
CO2	1.05	1.05	-
SO2	1.05		
NMVOC total	1.50		
NOx, N2O	1.50		1.40
CH4, NH3	1.50		1.20
Individual hydrocarbons	1.50	2.00	
Pm>10	1.50	1.50	
Pm10	2.00	2.00	
Pm2.5	3.00	3.00	
Polycyclic aromatic hydrocarbons (PAH)	3.00		
CO, heavy metals	5.00		
Inorganic emissions, others	-	1.50	
Radionuclides (e.g. Radon-222)	-	3.00	
Pollutants emitted to soil:			
Oil, hydrocarbon total		1.50	
Heavy metals		1.50	1.50
Pesticides			1.20

Figure 37. Basic uncertainty factors table.

Appendix 6: Uncertainty factor for each pedigree criterion

	Indicator Score	1	2	3	4	5
Default uncertainty factors (contributing to the square of the geometric standard deviation) applied in conjuction with the pedigree matrix)	**Reliability**	1.00	1.05	1.10	1.20	1.50
	Completeness	1.00	1.02	1.05	1.10	1.20
	Temporal correlation	1.00	1.03	1.10	1.20	1.50
	Geographical correlation	1.00	1.01	1.02	-	1.10
	Further technological correlation	1.00	-	1.20	1.50	2.00
	Sample size	1.00	1.02	1.05	1.10	1.20

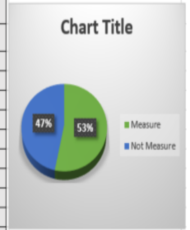
Figure 38. Uncertainty factors table.

Appendix 7: Full Tables of the Empirically-Based Uncertainty Factor Approach Method

INVENTORY — EMPIRICALLY -BASED UNCERTAINTY FACTORS APPROACH METHOD

Input	Completeness	Temporal Correlation	Geographical Correlation	Technological Correlation	Basic uncertainty ln(Ub)^2	Total uncertainty factors (UF) Ʃ(ln(UF)^2	sqrt(UF)	SDg95	Verdict	Measure or Not Measure
Electrical energy from public grid (France)	0.000390	0.000000	0.000000	0.000000	0.00238	0.00277	0.05263535	1.054045218	Very low uncertainty	
Heat Production, Propane	0.000000	0.000000	0.000392	0.000000	0.00238	0.00515	0.071780778	1.074419782	Very low uncertainty	
Acetone or Isopropyl Alcohol	0.000390	0.000000	0.000099	0.000000	0.00238	0.00525	0.072449983	1.075139029	Very low uncertainty	
Wire feedstock (Steel, Ti, Cu, etc); raw material	0.000000	0.000000	0.000392	0.033241	0.00238	0.03839	0.195942543	1.216457009	Low uncertainty	
Contact tips (replaced every 2h for a 40h print)	0.002381	0.009084	0.000392	0.164400	0.00238	0.21188	0.460300967	1.584550811	High uncertainty	measure
Substrate material; raw material	0.000390	0.009084	0.000099	0.033241	0.00238	0.04757	0.218115749	1.24373102	Low uncertainty	
Lubricating oil and/or Cooling fluid	0.000390	0.000000	0.000099	0.000000	1.20695	1.20982	1.099917252	3.003917445	Extremely high uncertainty	measure
Shielding gas (Ar/CO2)	0.000390	0.000000	0.000099	0.000000	0.00238	0.00525	0.072449983	1.075139029	Very low uncertainty	
Compressed Air	0.000000	0.000874	0.000099	0.000392	0.00238	0.00375	0.061200328	1.063111864	Very low uncertainty	
CNC Machining (including tools)	0.000390	0.009084	0.000392	0.000392	1.20695	1.22629	1.107380224	3.026419459	Extremely high uncertainty	measure
Water	0.000000	0.009084	0.000099	0.000000	0.16440	0.17358	0.416635277	1.516849182	High uncertainty	measure
CMT Welding Station	0.009084	0.164400	0.000392	0.164400	1.20695	1.55431	1.246719279	3.478910879	Extremely high uncertainty	measure
Heating Oven	0.009084	0.164400	0.000000	0.033241	1.20695	1.42276	1.192794182	3.296278755	Extremely high uncertainty	measure
Fume extractor	0.009084	0.164400	0.000392	0.033241	1.20695	1.42315	1.192958491	3.296820407	Extremely high uncertainty	measure
Testing machine/equipment	0.009084	0.164400	0.000392	0.033241	1.20695	1.42315	1.192958491	3.296820407	Extremely high uncertainty	measure

Decision	
Measure	8
Not Measure	7



Output	Completeness	Temporal Correlation	Geographical Correlation	Technological Correlation	Basic uncertainty ln(Ϭb)^2	Total uncertainty factors (UF) Ʃ(ln(UF)^2	sqrt(UF)	SDg95	Verdict	Measure or Not Measure
Waste Substrate Structure	0.009084	0.0000	0.0000	0.033240	0.00238	0.05379	0.231922401	1.261021871	Moderate uncertainty	measure
Worn out parts	0.000390	0.0000	0.000099	0.033240	0.00238	0.04519	0.212586453	1.23687304	Low uncertainty	
Heat emissions; emissions to atmosphere	0.000390	0.0000	0.000099	0.000000	0.00238	0.00525	0.072449983	1.075139029	Very low uncertainty	
Waste solvent; emissions to water	0.002381	0.0000	0.000392	0.033240	0.16440	0.20950	0.457710011	1.580450623	High uncertainty	measure
Packaging waste	0.000390	0.0000	0.000099	0.033240	0.00238	0.04519	0.212586453	1.23687304	Low uncertainty	
Scrap wire waste	0.000390	0.0000	0.000099	0.033240	0.00238	0.03849	0.196186136	1.216753366	Low uncertainty	
Metal fumes/spatter; emissions to atm, water, land	0.000000	0.0000	0.0000	0.000000	0.48045	0.48954	0.699669218	2.013086703	Extremely high uncertainty	measure
Welding fumes; emissions to atmosphere	0.002381	0.0000	0.000392	0.033240	0.48045	0.52555	0.724947939	2.06462361	Extremely high uncertainty	measure
Metal dust/chips	0.002381	0.0000	0.000392	0.033240	0.48045	0.52555	0.724947939	2.06462361	Extremely high uncertainty	measure
Grease and oil waste; emissions to water	0.002381	0.0000	0.000392	0.033240	0.16440	0.20950	0.457710011	1.580450623	High uncertainty	measure
Gaseous emissions (Particulate matter, SOx, NOx, Ph)	0.000000	0.0000	0.0000	0.000000	0.48045	0.48045	0.693147181	2.00000000	Very high uncertainty	measure
Used KUKA Robot	0.009084	0.164400	0.000392	0.009084	1.20695	1.39899	1.182790328	3.263467656	Extremely high uncertainty	measure
Used Welding Unit	0.009084	0.164400	0.009084	0.033240	1.20695	1.43184	1.196595571	3.308833039	Extremely high uncertainty	measure
Used Extraction hose	0.009084	0.164400	0.000392	0.033240	1.20695	1.42315	1.192958072	3.296819025	Extremely high uncertainty	measure
Used Heating Oven	0.009084	0.164400	0.000392	0.033240	1.20695	1.42315	1.192958072	3.296819025	Extremely high uncertainty	measure

Decision	
Measure	11
Not Measure	4

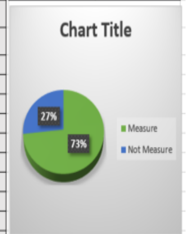


Figure 39. Uncertainty factors calculation by pedigree matrix method.