System Approach to Investigate Environmental Footprint and Cost Tradeoffs in Additive Manufacturing

by

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B.S. Chemical Engineering
Oregon State University (2019)

Submitted to the System Design and Management Program
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE IN ENGINEERING AND MANAGEMENT

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

February 2024

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ABSTRACT

As additive manufacturing (AM) continues to grow and show potential for efficient resource utilization and product lifecycle, it represents a promising technology for the green industrial transformation needed to achieve Net Zero Emissions by 2050. However, the environmental impact of AM remains unclear, given its diverse applications and the historical emphasis on cost and quality as primary adoption drivers. Pressured by climate change, AM manufacturers lack quantitative tools to balance the technology's complexity, environmental impact, and economic value.

This thesis demonstrates the use of system modeling methodologies to help AM manufacturers navigate these tradeoffs and make data-driven decisions to scale their service. After exploring the policy landscape impacting manufacturing and reviewing the latest developments in AM cost modeling and environmental impact assessment, a case study on an AM service unit in the sporting goods industry is used to illustrate the methodologies. A tradespace analysis compares the value of HP's MultiJet Fusion technology to injection molding (IM) across various product characteristics and lifecycle decisions, and a flexible design analysis evaluates various investment decisions, considering uncertainties from the market and technology.

For the case studied (and assumptions used), the tradespace analysis reveals a 75% lower environmental footprint (EF) per part using AM compared to IM, while IM yields a 97% unit cost saving. Maximizing build capacity with small, uniform parts in locations with low-footprint energy increases AM's economic and environmental value, suggesting that opposite product attributes and lifecycle decisions constitute development areas. The flexible design analysis, conducted for the specific AM service unit, shows that transitioning with added capacity to a larger rental facility with solar panels yields a 37% lower EF than maintaining current operations, and waiting to move to the larger facility until the demand aligns with added capacity generate a 96-137% increased NPV. These trends lead to the recommendation to transition the existing

capacity to a larger rental facility with solar panels and wait for increased demand to invest in additional capacity.

These insights affirm the effectiveness of system modeling methodologies in guiding AM service providers by balancing financial and environmental factors. By introducing the application of these techniques in the AM context, this study establishes a baseline and identifies gaps to bridge for improved model accuracy. The approach developed in this work can be applied to different cases to quantitatively explore strategic options for technology investment and scaling to meet financial and environmental sustainability goals.

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Acknowledgments

I would like first to acknowledge and give my warmest thanks to Philippe Seille, Julien Guillen, Gregoire Mercusot, and the entire Add Lab team at Decathlon. Philippe and Julien, thank you for connecting with me back in September and enabling me to apply my thesis vision to add value to a real company. Your trust and humor directly made me feel welcome on the team. Gregoire, I am deeply grateful for the time you gave me every week, for being the best collaborator and thought partner I could have asked for, and for being a great tour guide during my visit to Lille. It has been a pleasure working with a team so dedicated, engaged, and enjoyable to collaborate with.

Secondly, I would like to express my sincere gratitude to my thesis advisors, Afreen Siddiqi and Bruce Cameron. Afreen, thank you for onboarding this journey as my primary thesis advisor and giving me the inspiration for my thesis topic. Your patience, flexibility, guidance, and expertise have been key to the well-roundedness and success of this thesis. Thank you for helping me find clarity when the process became overwhelming or frustrating. Bruce, thank you for bringing a compelling eye to my work. Your feedback and insights always challenged me to think deeper or differently about an approach, analysis, or recommendation, adding tremendous rigor to my work. In the same vein of supporting my thesis work, I would also like to give my thanks to Richard de Neufville for teaching his class on flexible design analysis, a concept and method that I hope to use for the rest of my career. Thank you for taking the time to dive into this topic and help me frame my approach even if you were not one of my official thesis advisors.

Third, I would like to share my gratitude to the SDM staff and cohort. You turned this year and a half into the richest experience I could have asked for. This journey opened my eyes to the breadth of this world, offered me new perspectives, and gave me lifelong friendships. I had never expected to find a cohort so humble, diverse, kind, and caring after moving across the country and starting my journey at MIT.

Finally, I would like to thank my partner, Jose, for being my rock and biggest cheerleader throughout this master's program. Your consistency and patience through the highs and lows enabled me to experience this chapter of my life to the fullest. Thank you for always being willing to discuss ideas and approaches to help me advance in my work. I am also grateful to my family for always supporting me from far away and for sacrificing our rare quality time in support of this thesis's finalization.

This journey, enabled by the support of the 3D team at HP whom I also want to recognize here, has been a life-changing experience. I hope to keep and carry the diversity of perspectives I have gained and find ways to apply these new mental models throughout the rest of my life journey.

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1. Introduction

1.1. Motivation

In recent years, the landscape of manufacturing has witnessed a paradigm shift with the adoption of digital and advanced technologies such as additive manufacturing (AM) [1] and the pressure to accelerate the green industrial transformation [2]. Responsible for a quarter of the energy-related carbon emissions in 2022, the industry sector is compelled to aggressively pivot towards more sustainable practices in order to achieve Net Zero Emissions (NZE) by 2050 [3]. Based on the updated NZE roadmap, switching to electricity, and improving technology, material, and energy efficiency will constitute a critical improvement toward this NZE goal [3].

Additive manufacturing represents a promising solution to supporting this class of efforts [4], [5], [6], even though the technology's impact on the environment varies heavily by application and is still unclear [7]. Its potential benefits span across more efficient resource consumption, reduced waste generation, and overall improvement of product life cycle and supply chain [8].

Surveys have shown, however, that AM adoption is historically not driven by its sustainability benefits but rather by economic motives [9]. In fact, this technology, often synonymous with 3D printing, has disrupted traditional manufacturing processes [10], [11] by opening up new avenues for businesses to innovate [12]. AM offers unique advantages regarding rapid design optimization, customization, and production efficiency [13]. Its ability to construct complex geometries layer by layer from a digital model reduces material waste but also enables the creation of intricate and lightweight structures that may be challenging or impossible to produce using conventional manufacturing methods [14], [15]. Additionally, AM facilitates on-demand, distributed production, fostering flexibility in design iterations and agility in supply chains [8], [16]. In 2022, the AM industry grew by 18.3%, reaching a total value of $18.0B, and it is projected to grow beyond $100B by 2032 [17].

Amidst this seemingly transformative era, the burgeoning adoption of 3D printing is not without its challenges and doubts. Given the low maturity of the technology for mainstream applications [15], the industry grapples with issues such as material limitations [13], manufacturing speed and quality [18], process standardization [19], and the need for new workforce training [11]. An even greater roadblock lies in the need to transform and rethink traditional business and operational models [4], [20]. Despite the slow large-scale adoption caused by these challenges and the feeling of disillusionment from misleading expectations some users have experienced, the technology is on its path to evolve into a viable, large-scale manufacturing method thanks to successful companies in the medical, consumer goods, or automotive industry [13], [17], [21].

Between the ongoing, complex development of AM and the urgency climate change presents, 3D printing companies and users face increased pressure to embed sustainability as a core part of their strategy and reconcile the economic benefits of additive manufacturing with the imperative to reduce environmental impact. Traditional decision-making models may fall short in addressing the multifaceted nature of these choices, necessitating a more quantitative and integrative approach. This approach would not only enhance financial performance, but also integrate sustainable practices seamlessly into the strategic fabric of business units offering AM services. Manufacturing companies thinking more holistically could enable additive manufacturing to grow successfully and realize its full potential across various sectors.

1.2. Research Objectives

Additive manufacturing service companies experiencing this growing pressure must strike a delicate balance between strategic alignment, financial viability, and environmental sustainability. This thesis aims to use system modeling and analysis tools to help manufacturers make informed, data-driven decisions on the strategic development of their AM services. This work will encompass the following objectives to achieve this general intent:

1. Describe the current landscape of policies influencing the sustainability goals companies set for themselves and summarize the status of AM and existing financial and environmental tools that can help 3D printing users define an AM strategy for their business.
2. Evaluate whether using quantitative system analysis and modeling approaches can provide insights to a company developing an AM strategy with a case study in the consumer goods industry.
3. Build a tradespace analysis and a flexible design analysis model representing the case and leading to data-driven recommendations on specific products, lifecycle paths, or investment decisions impacting environmental and financial performance.

1.3. Thesis Structure

This thesis is organized into seven chapters. Chapter 1 introduces the context around additive manufacturing and sustainability, as well as the scope this thesis covers. Chapter 2 dives into a literature review of the policy landscape around environmental sustainability in industry, the AM market, and the tools and studies that exist to assess the financial and environmental performance of the technology, finishing with a brief overview of system modeling methodologies and their purpose. Chapters 3 through 6 encompass the case study used to examine the value of each system approach used in this work. These chapters work from introducing the case study company and the problem statement, to documenting the result of applying the system modeling approaches to the case study, to providing a recommendation and next steps for the case company. Chapter 7 provides conclusions and recommendations for any companies using additive manufacturing technologies more generally to help them define the appropriate approach to establishing a strategy that aligns with their environmental and financial goals. **Figure 1** shows the flow of these chapters, highlighting what to expect from this thesis work.

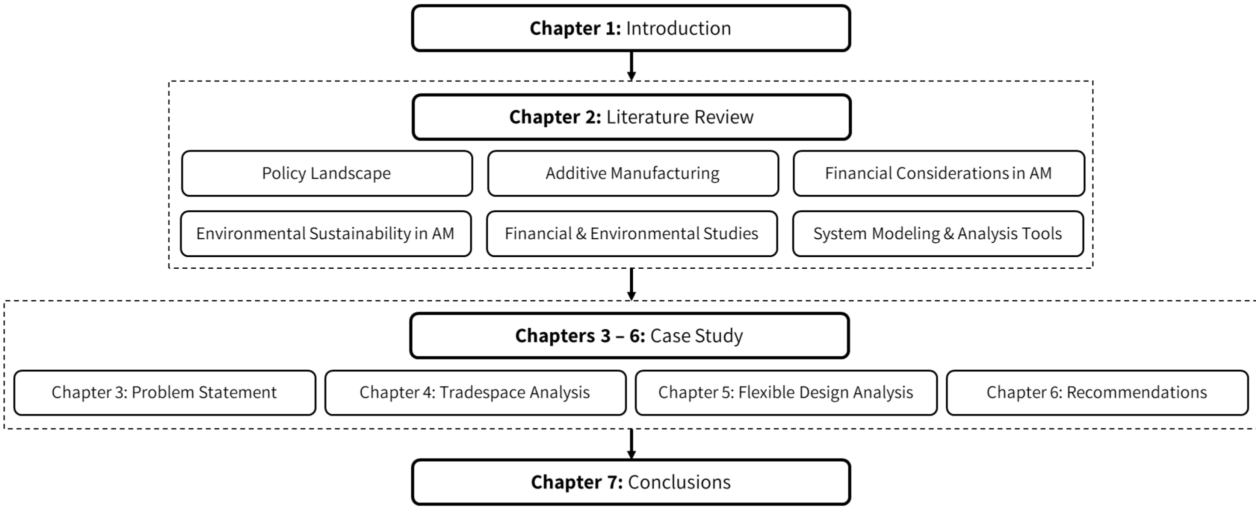

Figure 1. *Thesis structure.*

2. Literature Review

Before diving into a case study illustrating the use of system modeling and analysis methods to guide decision-making for a financially and environmentally sustainable AM strategy, it is important to provide context around six major areas. First, an overview of the global sustainability goals and policies urging the green industrial revolution is presented. The second section summarizes the history, processes, and current market situation of additive manufacturing. The third and fourth sections gather the latest findings and recommendations from the literature on cost models and environmental assessment methodologies for AM. Fifth, a review of research work integrating AM's financial and environmental aspects to support decision-making is performed. Finally, the literature review ends with a short introduction to systems tools and methodologies.

2.1. Policy, Regulation, and Standard Landscape

Understanding the policy, regulatory, and standardization landscape influencing the push for sustainable manufacturing and how it is applied to the development and adoption of additive manufacturing will contextualize the work performed in this project. This section will provide an overview of the global sustainability initiatives that have emerged, key regional climate and energy policies impacting the industry sector, and the current state of standards around AM.

2.1.1. Global Sustainability Initiatives Affecting Manufacturing

Several global initiatives are at the root of the environmental policies and regulations impacting the manufacturing industry. They also serve as references for international companies to define their sustainability strategy and targets. The first major blueprint is the United Nations' 17 Sustainable Development Goals (SDGs) stemming from the 2030 Agenda for Sustainable Development and aiming at mobilizing all nations towards achieving short and long-term peace and prosperity for people and the planet [22]. Adopting sustainable manufacturing practices directly relates to 10 of the 17 goals, including (6) clean water and sanitation, (7) affordable and clean energy, (8) decent work and economic growth, (9) industry, innovation, and infrastructure, (11) sustainable cities and communities, (12) responsible consumption and production, (13) climate action, (14) life below water, (15) life on land, and (17) partnerships for the goals.

The second widely adopted framework stems from the Paris Agreement established in 2015 at the COP21 in Paris to support the SDGs' achievement [23]. The Agreement is built around three main goals consisting of:

1. Cutting global emissions to limit the global temperature rise below 2ºC above pre-industrial levels while truly aiming for below 1.5ºC.
2. Regularly assessing progress using an enhanced transparency framework.

3. Providing financial support to developing countries for climate change mitigation and adaptation.

So far, 195 parties have joined the agreement, and progress has been made with the increase of competitive low or zero-carbon solutions and markets, but much more effort is needed to achieve the goals [24].

To support businesses in achieving the goals of the Paris Agreement, a set of sector-specific emission reduction roadmaps have been developed via the Science-Based Targets Initiative (SBTi) [25]. These roadmaps contain criteria and recommendations for various industry sectors based on different levels of scope (1 - direct emissions from own or controlled sources, 2 – indirect emissions from the generation of purchased energy, and 3 – all indirect emissions that do not fall into scope 2 but are part of the business value chain, downstream or upstream) [26]. The Greenhouse Gas Protocol is a fellow standardization framework that provides detailed GHG emissions accounting and reporting guidelines based on these scope levels [27].

The Net Zero Emissions by 2050 Scenario is another pathway that was established to achieve energy-related SDGs [28]. It involves deploying a large portfolio of clean energy technologies without collateral impacts, coordinating policies and incentives to accelerate change while maintaining stability and security, and aiming for fair and effective global cooperation. The European Green Deal is a roadmap specific to Europe to achieve zero emissions by 2050 [29]. It also aims to decouple economic growth from resource consumption and ensure all people and countries are engaged and supported [30]. In 2021, with the Fit for 55 Package, the EU adapted its plan by targeting to reduce emissions by 55% by 2030 compared to 1990 levels to move closer to its goal for 2050. This plan impacts many sectors beyond industrial manufacturing, including transportation, energy, and infrastructure [31].

2.1.2. Regional Climate Policies Relating to Manufacturing

Policies and regulations affecting the manufacturing sector are often intertwined with energy- and emissions-related policies. In fact, the industry sector emitted a quarter of the global energy system emissions in 2022, while energy systems themselves represented three-quarter of all GHG emissions that same year, making it a major area of opportunity for improved sustainability [3], [32]. Some examples of initiatives aiming at increasing energy efficiency in the industrial sector include raising the price of industrial emissions (as many nations, including Canada, Korea, China, and the European Union, are doing [3]) and providing financial support to promote innovative technologies and projects that will lower the carbon emissions (such as the EU Innovation Fund investing about €40B between 2020 and 2030 in Europe-specific efforts [33]).

Zooming in on Europe, since environmental regulations are often more stringent there, two primary initiatives, the Green Deal Industrial Plan and the Net Zero Industrial Plan, have been initiated as part of the European Green Deal. The former is a plan developed to build a supportive environment to scale the EU's manufacturing capabilities for net-zero technologies [34]. It includes simplifying the regulatory environment, accelerating access to funding, developing a skilled workforce, and promoting global cooperation and open trade. The Net-Zero Industry Act is a sub-part of the Green Deal Industrial Plan and focuses on scaling up the manufacturing of clean technologies in Europe. It involves actions such as reducing administrative burden, simplifying the permitting process, pushing for CO2 capture by setting a target for 2030, and increasing market accessibility, skill enhancement, and information sharing [35]. In the United States, the Inflation Reduction Act (IRA) will provide $6B to reduce industrial emissions through the development of clean technologies [36]. Other countries such as Japan, the UK, India, and China have also developed their own industrial strategy to meet the Net-Zero Emission goals [3].

Beyond emission- and energy-targeted plans, the manufacturing sector is also impacted by climate initiatives revolving around the topic of circularity, which consists of always keeping materials in circulation to avoid waste [37]. This concept matters for manufacturers because it relies on product design improvements to enable resource recoverability and sustainable consumption via any of the 9Rs (refuse, reduce, reuse, repair, refurbish, remanufacture, repurpose, recycle, and recover [38]). As part of the European Green Deal, in 2020, the EU launched a circular economy action plan to make Europe cleaner [39]. This plan contains a list of 35 actions and describes policies and strategies affecting the chemicals, plastics, textiles, and industrial sectors. The U.S. Environmental Protection Agency (EPA) as well has published various circular economy strategies in collaboration with the National Institute of Standards and Technology (NIST) and the Department of Energy (DoE) [40]. These actions focus on food and organic waste reduction and recycling, plastic pollution prevention, and the creation of a national recycling strategy.

Additive manufacturing has been recognized as a potential solution to satisfy these initiatives. According to a 2023 report published by the European Commission on advanced manufacturing research and innovation, AM represented the primary technology investment in terms of project count by the European Institute of Innovation and Technology (EIT) [41]. In the US, in 2022, the Bidden-Harris administration announced the launch of AM Forward [42]. With this program, five major US original equipment manufacturers committed to bringing technical assistance and workforce training to suppliers, and the government agreed to support this by coordinating small and medium enterprises' access to programs providing capital, labor, and research investments.

2.1.3. Standards for AM

To support the adoption of AM and establish industry knowledge, the International Organization for Standardization (ISO) and the American Society for Testing and Materials (ASTM) have been collaborating to develop more standards to align terminology, measure the performance of various AM processes, provide design recommendations to users, qualify the quality of end products, and offer common calibration methods for major AM systems [43]. Standards for applications where it is critical, such as aerospace, transportation, infrastructure, and medical industries, are available. Due to the number of materials, processes, and applications in AM, there is a need to develop specific standards rather than generic ones. More work is needed, but the ISO/ASTM collaboration is promising for the global, cross-industry deployment of AM [19].

Because the adoption of AM is starting to alter production processes profoundly, there is a push for policymakers to accelerate the integration of the regulatory landscape with AM technology [14]. The increasing literature on AM processes and their impact on sustainability should enable policy makers and researchers to have access to more information and data to develop standards and goals aiming at achieving sustainability targets [44]. This policy context should serve as a reference point and motivation for further sustainability analyses on manufacturing technologies such as AM.

2.2. Additive Manufacturing

2.2.1. Definition and History

Additive manufacturing is defined as the process of translating, layer-by-layer, 3D model data into a physical part using material in the form of filament, pellets, powder, or sheets [45]. Per its name, as opposed to conventional methods, AM is additive rather than subtractive. The birth of this technology was closely tied to the advancement in computer-aided design (CAD) and dates from the 1980s with the invention of the first stereolithography (SLA) machine capable of curing liquid polymer using lasers to form a three-dimensional object [46]. This invention translated into the first commercial SLA system from 3D Systems, which was launched in 1987 [47]. Throughout its evolution, various terminologies have been used for the technology, including layered manufacturing (LM), rapid prototyping (RP), rapid manufacturing (RM), rapid tooling (RT), freeform fabrication, 3D printing (3DP), and additive manufacturing (AM) [48], [49]. In this thesis, 3D printing and additive manufacturing will be used interchangeably.

2.2.2. AM Processes

Between the 1980s and now, many additive manufacturing technologies have emerged, leading to the creation of seven categories developed by ASTM [45]. A summary of each category, along with the process description, the types of technologies embedded in each classification, and the major system manufacturers, is provided below [8], [18], [50]:

1. **Binder jetting (BJ):** Use of a binding agent to join material powder particles together. Major BJ printer manufacturers include Hewlett-Packard and Desktop Metal.
2. **Directed energy deposition (DED):** Use of an energy source to melt material as it is deposited. The energy source can be a laser (Laser Engineered NetShaping – LENS or laser deposition technology – LDT), or an electron beam (electron beam additive manufacturing – EBAM). Major DED printer manufacturers include Sciaky (EBAM), RPM Innovations (LDT), and Optomec (LENS).
3. **Material extrusion (MEX):** Process where material is dispensed through a nozzle or orifice. The process can be done with heat (fused filament fabrication – FFF or fused deposition modeling – FDM) or without (direct ink writing – DIW). Major material extrusion printer manufacturers include Stratasys, Ultimaker, and Markforged.
4. **Material jetting (MJT):** Process where material droplets are selectively deposited. The material deposition can be continuous or follow the Drop on Demand (DOD) approach. Major material jetting system manufacturers include 3D Systems and Stratasys.
5. **Powder bed fusion (PBF):** Use of an energy source to fuse material powder particles together. The energy source can be a laser (selective laser sintering – SLS, selective laser melting – SLM, or direct metal laser sintering - DMLS), an electron beam (electron beam melting – EBM), or infrared light in the presence of a fusing agent (multi-jet fusion – MJF). Major PBF system manufacturers include EOS (SLS), 3D Systems (SLS), Formlabs (SLS), and Hewlett-Packard (MJF).
6. **Sheet lamination:** Often called laminated object manufacturing (LOM), this process consists in binding sheets of material together using a binding adhesive or ultrasonic (ultrasonic additive manufacturing – UAM). This process is hybrid since it requires CNC milling or laser cutting to form the object's shape. One of the only systems manufacturers left is Fabrisonic (UAM).
7. **Vat photopolymerization (VPP):** Use of an energy source to cure liquid material. The energy source can be a laser (stereolithography – SLA), a projector (direct light processing – DLP), or LED in the presence of oxygen (continuous direct light processing – CDLP). Major VPP system manufacturers include 3D Systems (SLA) and Carbon (DLP).

For in-house use, market surveys from 2021 [51] showed that MEX (FDM/FFF) was the most used 3D process, followed by VPP (SLA and DLP/LCD). Regarding external services, PBF was the most demanded process category (SLS, followed by MJF, and DMLS/SLM).

2.2.3. Market Adoption and Applications

As mentioned in the introduction, the market for AM has reached a value of $18.0B, growing by 18.3% in 2022, with the ten largest manufacturers representing 15.1% [17]. The past and future market trends are shown in **Figure 2** below and account for both AM products and services combined. Multiple drivers drove the takeoff in growth starting around 2010 and its continuity until today. One driver was the expiration of AM technique patents, such as Stratasys' fused filament fabrication patent in 2009, which enabled new players to make and sell their own FDM systems without risking IP infringements any longer [52]. Another reason is simply the technical development of the technology, including its improvement in speed, control, material availability, and complementary infrastructure (i.e., software, post-processing technologies, generative design, as well as AM-specific standards) [13]. Finally, the economic value of AM is becoming more concrete by enabling a faster and more efficient product development process and rapid access to small-batch manufacturing for tooling, spare parts, repairs, or very complex and customized pieces [1].

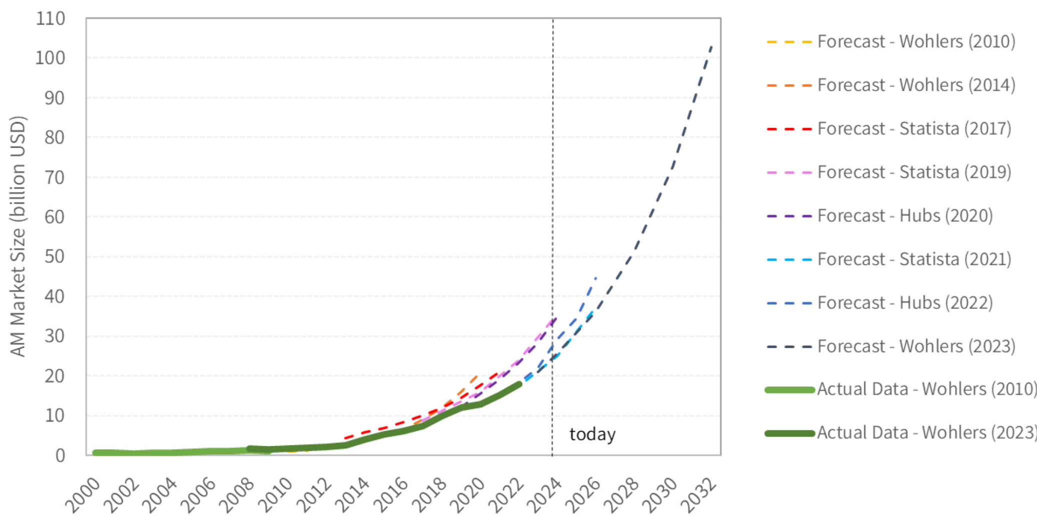

Figure 2. Historical and projected AM market value. Sources mentioned in the legend.

Many industries such as consumer goods (e.g., Smith[1]), government/military (e.g., AM Forward[2]), aerospace (e.g., Relativity[3]), automotive (e.g., BMW[4]), medical/dental (e.g., SmileDirectClub[5]), machinery (e.g., John Deere[6]), power/energy (e.g., Sakuu[7]), architecture/construction (e.g., ICON[8]), or education (e.g., MIT Media Lab[9]) are tapping into

[1] https://time.com/collection/best-inventions-2022/6229823/smithimprint/

[2] https://www.whitehouse.gov/cea/written-materials/2022/05/09/using-additive-manufacturing-to-improve-supply-chain-resilience-and-bolster-small-and-mid-size-firms/

[3] https://www.relativityspace.com/

[4] https://www.press.bmwgroup.com/global/article/detail/T0286895EN/a-million-printed-components-in-just-ten-years:-bmw-group-makes-increasing-use-of-3d-printing?language=en

[5] https://press.hp.com/us/en/press-releases/2019/hp-and-smile-direct-club-collaborate-on-largest--multi-jet-fusion-3d-production-factory-in-the-us.html

[6] https://www.forbes.com/sites/carolynschwaar/2022/12/21/john-deere-turns-to-3d-printing-more-efficient-engine-parts/

[7] https://www.sakuu.com/news/sakuu-announces-successful-3d-printing-of-fully-fu

[8] https://www.iconbuild.com/projects/el-cosmico

[9] https://www.media.mit.edu/projects/water-based-additive-manufacturing/overview/

these various processes to produce a variety of applications ranging from prototypes, components, or final production parts. Even though the technology was initially used solely for prototyping, the use of AM for end-use applications has grown and now represents the majority of applications printed by 3D manufacturers. This trend is supported by an increase in the number of industrial system manufacturers (7.5% between 2021 and 2022) and an increase in the number of industrial systems sold (12.1% between 2021 and 2022) [17]. Instead of growing an AM capability in-house, many companies rely on AM service bureaus to run their production. In 2022, independent service bureau part sales grew by 20.4% since 2021 [17].

In terms of AM materials, sales reached $3.3B in 2022, representing an increase of 25.5% since 2021 [17]. Various material types are available, including photopolymer resins, polymer powders and filaments, metals, ceramics, glass, paper, wood, waxes, and other composite materials. Polymer powders represent 38% of the market, photopolymers and polymer filaments 21%, and metal material 18% even though metal systems have been on the market for half of the industry's existence [17].

These upward trends show that more and more companies have recognized the potential of additive manufacturing. However, many decision drivers still impact adoption. This thesis will focus on the financial and environmental factors affecting a company's choices for implementing and deploying the technology.

2.3. Financial Considerations in Additive Manufacturing

Literature on cost modeling for additive manufacturing, then called layered manufacturing, was initiated by Alexander et al. in 1998 [53]. Since then, multiple approaches, methods, and model developments have emerged and been summarized through literature reviews [48], [49], [54], [55]. The major contributions in terms of approach and learning are presented in this section.

2.3.1. Cost Modeling Approaches Applied to AM

Over the past 25 years, various cost accounting scopes have been considered, evolving from process-oriented models only analyzing a single process and a single part to system-level models accounting for multiple parts and the infrastructure and impacts around the AM system [48]. The calculation techniques also evolved from intuitive, analogical, and parametric to analytical and big data models [48]. Each presents advantages and weaknesses: the earlier ones (intuitive, analogic, parametric) are fast and simple but prone to poor estimation and repeatability, while the later ones (analytical, big data) are more accurate and detailed but more complex to create and communicate. Across the literature reviewed, two main costing estimation techniques were employed to develop AM cost models in more detail:

1. **Activity-based costing (ABC):** this method was the first one applied to AM [56] and consists of assigning costs based on the activities and resources consumed by the

product or service. This method centers on the production process, which converts raw materials to finished products.

2. **Life cycle costing analysis (LCC or LCCA):** this method appeared later with Lindemann in 2012-13 [57] and differs from ABC by considering all costs associated with the product over its entire life cycle, from material extraction and design to distribution and disposal or recycling [58]. The scope and timeframe of this method are much larger than for ABC.

To account for the potentials of AM in design optimization, supply chain simplification, and lifecycle impact reduction, and make a more compelling case when comparing it to traditional manufacturing methods, some would argue that using the life cycle costing approach would be more adequate [59]. However, it is important to note that this accounting method requires an understanding of all the stakeholders involved throughout the product lifecycle and the inclusion of costs that are not necessarily accrued by the company manufacturing the goods.

2.3.2. AM Cost Model Evolution

The first body of work that constituted a baseline AM cost model was developed by Hopkinson and Dickens in 2003 [54]. They compared three additive manufacturing processes (SLA, FDM, and SLS) to injection molding in the context of high-volume and high-capacity utilization production. The unit costs were broken down into three direct costs (material, machine, and labor), and the overhead costs were ignored as the authors found their impact insignificant [60]. To challenge these assumptions, Ruffo et al. (2006) built an updated cost model following a full activity-based costing method and separated direct and indirect costs to estimate the unit cost of smaller production volumes at lower capacity utilization [56]. For the first time, unused material recycling and indirect overhead costs such as facility rent, energy, or ancillary equipment were considered. From there, multiple contributions using more and more advanced costing methodologies were made to augment the accuracy of AM cost models:

- An estimation model of the **print time**, a key driver of production costs, was further developed by Gibson et al. in 2010 [61].
- The impact of **build capacity utilization** and **part orientation** on **energy** consumption and emissions was better quantified through multiple studies [62], [63], [64], [65].
- **Post-processing** costs and broader **product lifecycle** costs were included in the model by Lindemann et al. (2012) using a time-driven activity-based costing approach [66], as well as Schröder et al. (2015) and Westerweel et al. (2018) [59], [67].
- The cost consideration of **mixed-component builds** rather than single-part production was modeled by Ruffo et al. (2007) [68] and Rickenbacher et al. (2013) [69].
- **Part design** activities and **redesign** were factored into the cost estimations by Schroder et al. (2015) [67] and Atzeni et al. (2010) [70], respectively.

- The implications of AM on the **supply chain** costs in centralized and distribution production scenarios were assessed by Holstrom et al. (2010) [71] and Khajavi et al. (2014) [72], and the decision of outsourcing or producing in-house was quantitatively guided by Ruffo et al. (2007) [73].
- An experimental study to understand the **economies of scale** in AM by better defining the relationship between production volume, capacity, and cost was published by Baumers et al. in 2019 [74].
- Operator **learning rate** [74] and **process failure** modes through the use of a "damage factor" [53] were quantified as costs by Baumers et al. (2019) and Ding et al. (2021).

Over the past two decades, AM cost models have evolved into more comprehensive ways to estimate financial drivers for strategic production planning and to help highlight areas of cost reduction for the technology. **Figure 3** summarizes the cost drivers for additive manufacturing according to lifecycle, total, pre-processing, production, and post-processing cost levels. Depending on the AM process to analyze, some cost parameters may be omitted, and the cost computation may vary.

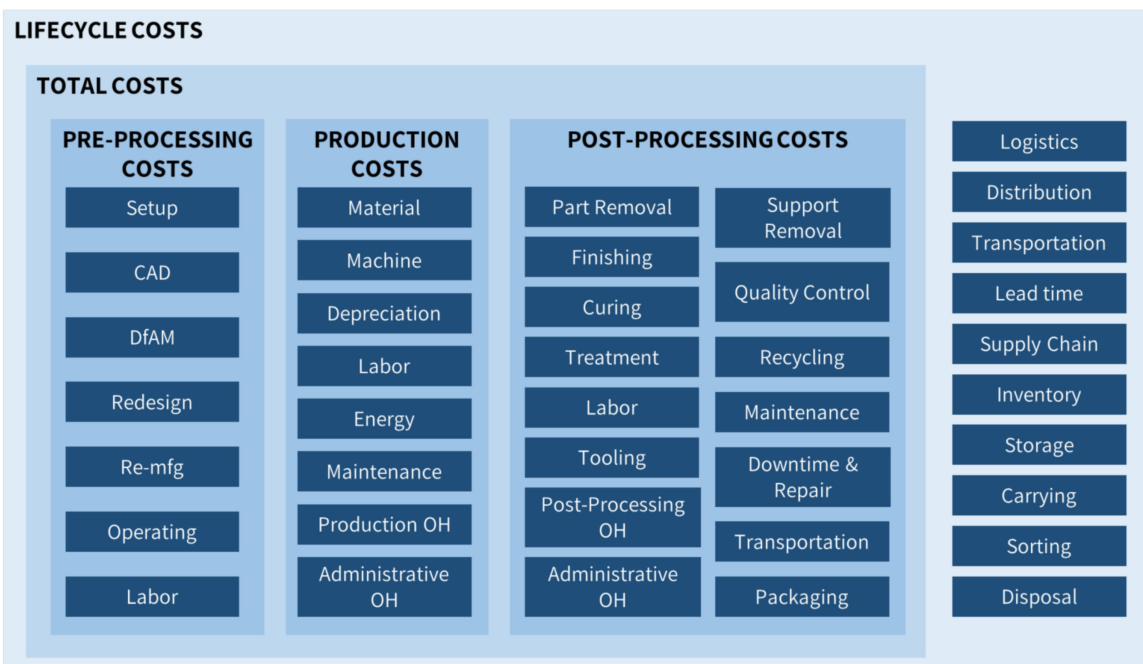

Figure 3. Summary of AM cost drivers based on lifecycle costs, total costs, pre-processing costs, production costs, and post-processing costs. Adapted from data gathered by [48].

2.3.3. Summary of Learnings on Cost Considerations for AM

A generalization of the learnings from these studies leads to the consensus that the economic value of AM generally lies in small-to-medium production volumes (i.e., 200 – 100,000 parts depending on the application) of builds filled with small, complex, or customized parts [61], [69],

[70], [74], [75]. Additionally, the technology offers benefits in the product development efforts as well as the supply chain and product lifecycle realms [54], [59], [67], [71], [72]. Already concluded in 2003 [60], machine and material costs are still significant cost drivers for the technology [17], [56], [66], [70]; however, the growing adoption of AM paired with part lightweighting efforts should lead to cost reduction for 3D materials [70]. Build volume and capacity utilization can also affect costs [62]. In fact, high throughput (i.e., number of parts per job) and high capacity utilization (i.e., number of parts fitting on the horizontal plane for a fixed build height) can lower unit costs in a sawtooth fashion, achieving economies of scale like traditional manufacturing [74]. In addition to these factors, labor costs stemming from pre- and post-processing also represent significant expenses for the technology [61]. However, they can be improved through the optimization of support structures [4], the natural learning rate of AM operators [74], and the automatization of the process [54].

Despite the lack of a general, versatile, web-based AM cost model that also takes into account the final product quality and uncertainty [48], [76], this progress has provided a good foundation for many AM service providers or users to develop their own internal cost calculators or launch commercial products, such as the AM Power Cost Calculator Tool[10]. The next step would be to integrate the cost of environmental sustainability to guide decision-makers holistically.

2.4. Environmental Sustainability in Additive Manufacturing

Unlike the research on AM cost models, the literature on the environmental sustainability of AM is more recent, showing an increase in number of publications starting around 2017 [4], [6], [77]. The external pressure of addressing climate change and the recent growth in AM adoption have triggered interest in assessing and mitigating the environmental impact associated with this technology [78]. A summary of the methods used to evaluate the environmental footprint of AM is introduced in this section, along with general insights on the potential and risk of AM in constituting a cleaner manufacturing technology than conventional methods.

2.4.1. Environmental Assessment Approaches Applied to AM

Somewhat parallel to cost accounting techniques, three major environmental impact assessment methods have been or could be applied to additive manufacturing as summarized by Lee (2023) [79]:

1. **Life Cycle Assessment (LCA)** is a standard method that was first published by ISO in 1997 [58] and consists of measuring the environmental impact of a product along its lifecycle from cradle to grave [80]. Various lengths of lifecycle can be modeled, including cradle-to-gate (raw material extraction to finished part postproduction), cradle-to-grave

[10] https://ampower.eu/tools/additive-manufacturing-cost-calculator/

(raw material extraction to end-of-life), gate-to-gate (consideration of a single process), or gate-to-grave (focus on end-of-life strategy). The method framework from ISO consists of four interactive phases: (1) goal and scope definition, where the intent of the study is stated; (2) inventory analysis, where all the needed inputs and outputs are collected; (3) impact assessment, where the inventory data is converted into an environmental impact factor such as climate change or land use; and (4) interpretation, where the results of the analysis are assessed to drive to improvement or change recommendations [58], [80]. During phase 3, impact assessment (LCIA), the inventory inputs and outputs can be assigned to 18 different *impact* categories (called midpoints), which then get classified into three major *damage* categories (called endpoints): natural resource impacts, abiotic ecosystem impacts, or potential human health and ecotoxicity impacts [81]. Once classified, optional normalization and weighing steps may follow. It is important to note here that many models have been developed to perform these analysis steps, and each considers a different combination and number of impact categories. Some popular methods include ReCiPe [82], Impact 2002+ [83], ILCD [84], Eco-Indicator 99, or IPCC. A list of all the models can be found in [58]. As an example application, the 3D manufacturer EOS, its customer YOU MAWO, and partner Fraunhofer EMI, used LCA to do a comparative study between 3D printed and conventionally manufactured eyewear [85]. Others, such as Tang et al (2016) [86], have adapted the traditional LCA model to embed the design optimization stage into the assessment to better account for one of the key values of AM.

2. **Material Flow Analysis (MFA)** can be defined as the study of the material flows in a system, going from raw material form to the disposal of its final form, maintaining mass balance principles [87]. Since all mass is conserved, MFA is closely linked to the concept of circularity. This analysis also follows several interactive steps: (1) problem and goal definition, (2) material, system boundaries, processes, and goods selection, (3) mass flow of goods and material concentration assessment, (4) material flow and stock calculation, (5) result visualization and decision implementation discussion [88]. Like LCA, many frameworks and models have been developed based on MFA. Commonly used examples include the Material Circularity Indicators (MCI) developed by the Ellen Macarthur Foundation and Ansys Granta [89] and the Circularity Transition Indicators (CTI) developed by the World Business Council for Sustainable Development [90]. As an example application to the AM context, Kulkarni et al. (2023) used MFA to capture the flow of materials involved in the creation of a brake caliper using AM [91].
3. Faulkner et al. (2014) adapted the lean manufacturing Value Stream Mapping into **Sustainable Value Stream Mapping (Sus-VSM)** in an industry case study to incorporate the environmental and societal sustainability elements into the value stream assessment [92]. This analysis follows the methodology of conventional VSM, where a

visual representation is used to observe the performance of a system studied and identify waste elimination opportunities. In this case, however, the performance metrics are adapted from monetary value to environmental and social impact indicators [92]. General steps include (1) goal and scope definition, (2) process family definition and examination, where a matrix of process steps versus parts produced is created and examined, (3) current value map creation, (4) future value map creation based on improvement identification, and (5) implementation plan creation [93].

Various software tools exist to support businesses with environmental impact assessment for AM. To pair with their cost calculator, AMPOWER, has developed and launched an AM sustainability calculator[11] for metal AM technologies, focusing on calculating the CO2 footprint for seven different AM metal processes. This tool draws from an analysis of each process step and includes post-processing, such as heat treatment and material recycling opportunities. It appears to be a simplified and adapted version of LCA. Granta EduPack Eco Audit Tool [94] is a tool that supports the selection of materials based on CO2 emission and energy consumption along the material life cycle analysis. A few AM processes (i.e., extrusion, wiredrawing) are available production options in the tool. However, more data must be collected and integrated to make this tool widely useable for the AM community. Finally, some have also attempted to integrate LCA into the CAD software to push sustainability-oriented decision-making at the design phase [95].

2.3.1. Summary of Learnings on Environmental Assessment for AM

Despite the recency of sustainability-oriented research for AM, multiple literature reviews have been published [4], [7], [14]. Following the Circular Transition Indicator methodology logic from the World Business Council for Sustainable Development (WBCSD) [90], to improve environmental sustainability, two main levers exist: (1) reducing the net consumption of resources entering (raw resource) and exiting (goods disposal) the system, and (2) maximizing the circularity of resources within the system by enabling the 9R's. A summary of the key findings on the influence of AM on these two levers is captured in **Table 1**.

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[11] https://ampower.eu/tools/additive-manufacturing-sustainability-calculator-metal/

Table 1. Advantages and disadvantages of AM on resource consumption and circularity.

	Resource Consumption	Circularity
ADVANTAGES OF AM	• Reduce waste leading to reduced material and energy consumption [8], [11], [14], [96] • Reduce need for support structure and tooling compared to traditional methods [14], [97] • Enable more efficient design of products reducing impact during product use phase [8], [11], [14], [96] • Enable more efficient supply chain with less transportation, or reduced inventory with on-demand spare parts [8], [11], [96]	• Enable repair, remanufacturing[12], recycling, and reuse [14], [98] • Promote the use of energy from renewable [99] • Use of biodegradable, reused, recycled, and advanced materials [100], [101] • Enable waste recovery [86], [102], [103] and valorization by transforming into input materials [104] • Encourage dematerialization [86], [102], [103] • Promote product life extension through design for product durability, upgradeability, performance and efficiency, and remanufacturing [86], [102], [103], [105] • Promote efficiencies and innovation through asset sharing [106] and use of big data and automation [107] thanks to its digital nature
WEAKNESSES OF AM	• Many processes require support structures, increasing material and energy consumption [4] • Part orientation in the build impacts material and energy consumption [108] • Energy efficiency varies based on AM processes, lifecycle scope, materials, designs, machines specifications, process parameters, energy conversion efficiency, part size/volumes [109] • Low production rate [110] and product quality [111], and need for post-processing increase energy use [97] • Energy-intensive material production process [97] • Toxicological risk (from ultrafine particles and volatile organic compounds) affecting environment and personnel [112]	• Lack of eco-friendly AM legislation and public policies [106] • Lack of strategic alignment between adoption of AM and circular business models [113] • Lack of skilled and experienced workers [114] • Lack of public responsibility regarding consumption and AM could drive consumerism [106], [115] • Lack of affordable unit cost [74] affecting adoption • Limitation on material cost and availability, material reuse lifespan, quality and scale of recycled or biodegradable materials [78], [106], [109], [116], [117], [118]
AREAS OF IMPROVEMENT	• Development of automated optimization methods to minimize support structure [108] • Effort to lower virgin material powder refresh rate [85] • Effort to lower material production footprint [85] • Reduction of packaging [85] • Development of method to identify optimal part orientation [108]	• Development of circular material strategies [105] such as recycling, reusing, repairing, and remanufacturing and understanding of the impact on material quality [98] • Effort to understand the operational and supply chain contingencies and causal loops affecting the adoption of AM in the CE context [119].
	• Move away from conventional design methods and adopt DfAM[13] to gain the full value of AM [120].	

[12] Remanufacturing consists in creating products from old products or parts of old products.

[13] DfAM = Design for Additive Manufacturing

As this summary table shows, a consensus on the impact of AM on environmental sustainability is lacking in the literature. Most of the research is still focused on energy and material consumption [121] or one particular issue rather than considering multiple aspects of environmental footprint and the tradeoffs between them [118]. Moreover, comparing various studies and drawing conclusions is difficult, given that too many AM parameters affect the results [109]. The influence of AM on circular economies is also unclear since the technology and customer awareness are still maturing, and the benefits of the technology on CE depend on its ability to overcome critical barriers mentioned in the disadvantages column [7], [119]. More empirical research is needed to show how companies use AM to support a circular economy [113]. On the bright side, initiatives are being taken, notably with the creation of the first global organization focusing on the technology's environmental benefits, the Additive Manufacturing Green Trade Association[14] (AMGTA), founded in 2019. The use of models is increasing and has been shown to help quantify the actual environmental impact of AM production and drive stakeholders to decisions [122], as seen with LCA studies performed in the production planning phase to weigh the adoption of AM instead [109] or in combination with [123] traditional technologies. More applications of these techniques will support the refinement and standardization of environmental sustainability frameworks specific to AM. Such efforts should lead to an effective integration of sustainable practices in the industry.

2.5. Integration of Financial and Environmental Considerations

Many studies focus on understanding the economic value of AM or its impact on sustainability. However, very few have explored the interaction between these topics [6], and even fewer offer practical tools and methods to inform decisions based on quantitative data. **Table 2** below is a collection of four research projects that have examined the interplay between these areas. The author, costing and environmental assessment methods used, key findings, and gaps in their approach are highlighted.

Table 2. *Summary of research integrating cost and environmental sustainability of AM.*

Research Project #1: Kazmer et al. (2023) [124]	
METHODS	<u>*Approach:*</u> • Parametric analysis, comparing polymer injection molding and material extrusion. • Varying production quantity, machine, mold and labor costs, and part size. <u>*Costs:*</u> • Machine (amortized per hour) • Mold (amortized per part) – *not applicable for AM* • Material, energy, and labor costs scaling with production quantity and mass/process time <u>*Environmental Impact:*</u> CO_2 emissions, conversion from USD, kg, and kWh • Machine (in kg CO_2 per USD)

[14] https://amgta.org/

	• Energy (in kg CO2 per kWh) • Material (in kg CO2 per kg) • Labor (in kg CO2 per USD)
FINDINGS	• Polymer injection molding uses less energy per kg of material than material extrusion and is more cost-effective and CO2-emission-effective than material extrusion above a production quantity of ~70,000 units. • Mold is the driver for IM in cost and CO2 emission (and breakeven quantity). • Labor is the cost and CO2-emission driver for AM. • Larger parts are ideal for IM (driven by wall thickness) but not for AM (driven by print time). • AM part quality along the Z axis was not good.
GAPS	• Used tensile specimens rather than end-use parts. • Used consumer-level material extrusion printer rather than industrial systems. • Only considering CO2 emissions as environmental impact. • Same operating hours per year for IM and AM. • Not accounting for mold maintenance cost or AM post-processing.
Research Project #2: Mecheter et al. (2023) [76]	
METHODS	*Approach:* • Comparison of CNC machining and direct metal laser sintering (DMLS) • Varying geometry complexity and shape size factors for a 3-part build • Use of Monte Carlo for sensitivity analysis on LCC input uncertainty *Cost:* LCC, cradle-to-gate, NPV over 8 years • AM: machine, pre-processing (setup, labor, tooling), processing (material, energy, inert gas), post-processing • CNC: machine, labor, setup, material, tooling, energy, machining *Environmental Impact:* LCA, Ecoinvent v3.8, ReCiPe, cradle-to-gate • Raw material extraction • Material processing • Part manufacturing
FINDINGS	• DMLS has most impact on human health (ReCiPe LCIA endpoint) while CNC has more impact on eco-system quality (other ReCiPe LCIA endpoint). • Electricity consumption is the driver for the environmental impact of both processes. • NPV of AM costs 91% more than CNC, AM is more suitable for highly complex parts while CNC is better for large sizes and low complexity. • AM cost is sensitive to processing and material costs. • AM needs more energy-efficient machines and dematerialization via design. • Part size is proportional to environmental impact.
GAPS	• Cradle-to-gate, not full lifecycle. • Doesn't consider post-processing in LCA. • Uncertainty only applied to LCC, not LCA. • Assigned same uncertainty (+/- 10% of normal distribution) for all cost variables.

Continued on the next page

Research Project #3: Moawad (2019) [125]	
METHODS	• Eco-efficiency method (XY profile) – *similar to tradespace showing cost metric on Y axis and environmental metric on X axis* [126], [127], [128] • Include uncertainty analysis with Monte Carlo simulation • Comparison of AM vs conventional manufacturing (CM) for aircraft application • Varying comparing various eco-designs *Cost:* LCC, distance-to-target[15], cradle-to-grave • AM: pre-production (material, CAD, argon), production (maintenance, cleaning, post-processing, finishing), use (fuel consumption and storage), EoL (landfill or recycling) • CM: pre-production (metal cylinder), production (production, waste, finishing), use (fuel consumption and storage), EoL (landfill or recycling) *Environmental Impact:* LCA, distance-to-target, cradle-to-grave, ReCiPe/IPCC 2013 • Material extraction and processing • Machine (with maintenance) • Consumables and utility • Post-processing • Transportation to assembly • Aircraft operations (not maintenance) • Transport to EoL • EoL (recycling, landfill)
FINDINGS	• AM is promising for the aircraft sector on environmental, economic, and eco-efficiency factors if design optimization is applied. • Distance traveled by aircraft, fuel consumption, production cost are the biggest uncertainty contributors. • Use phase of aircraft contributes to more than 95% of environmental impact (regardless of design). • AM is more energy-intensive than CM in the production phase. • Production costs are higher than use phase and waste management cost across designs. • For AM, post-processing costs are the largest contributor, while for CM, material costs are the largest.
GAPS	• Distance-to-target approach does not account for overall emissions. • Unique part (with different design versions), in unique build size (9 parts). • Exclusion of assembly step (since same for all scenarios) • Only uniform distributions used for uncertainty.

Continued on the next page

[15] Assess the distance between existing performance and desired performance rather than absolute value.

Research Project #4: Tagliaferri et al. (2019) [129]	
METHODS	*Approach:* • Comparing FDM, SLS, and MJF AM processes with polymer material (PA12). • Tested 6 parts with varying size/volume as 6 uniform builds of varying capacity. *Cost:* based on annual production quantity (calculated process time) and unit cost • Preliminary operations (CAD, printer preparation) • Production (material, energy) • Post-processing (support removal, part cleaning, labor) *Environmental Assessment*: LCA, SimaPro, cradle-to-grave, Eco-Indicator 99 • Material (raw material, support, chemical agents, etc.) • Energy (compressed air, electricity) • Disposal (excess powder, finished product) • Recovery and rework of excess raw material
FINDINGS	• FDM is the worst performing AM process compared to SLS and MJF in terms of cost and environmental impact due to slow production time (despite a larger build volume) and high energy consumption. • SLS (EOS) printer has the lowest cost (lower material cost or faster speed) and therefore is most profitable. • MJF printer has the fastest payback period (profit/purchase cost) and lowest impact potential thanks to lower energy consumption (although energy is still accounting for 60% of total impact). • Greatest impact across processes is depletion of resources (LCIA endpoint).
GAPS	• Cradle-to-gate: only considers costs associated with production, not the entire product lifecycle • No uncertainty analysis

These studies, which are only a subset of existing literature on AM's cost and environmental impacts, show interesting work and compelling conclusions. Some findings prove that the right manufacturing decision can lead to balanced and improved economic and environmental sustainability factors. These two objectives and needs are not always in conflict [108]. The methods covered in this section appear to be successful at including environmental and economic sustainability among objectives in the design of industrial products, processes, and services. However, based on the literature review performed by Mecheter et al. [76] and the assessment presented in the table above, five research gaps are observed:

1. There is a lack of analyses accounting for multiple sources of uncertainty at once [76]. Studies also tend to only consider uniform or normalized distributions rather than unique uncertainty behaviors specific to the nature of the parameter.
2. There is a lack of significance evaluation in tradeoff analysis leading to conclusions based on non-statistically proven differences [125].
3. Most of the literature considers either a single identical part with a unique size in a uniform build [76] or the same mixed build repeated over a certain period. These studies

are not representative of the capabilities of AM and present limited usefulness for service providers who produce a variety of builds containing different part sizes, shapes, and complexity and require different production volumes.

4. Very few studies consider the full cradle-to-grave assessment for both cost and environmental impact, often leaving out the product transportation, use, and end-of-life phases, and even fewer consider the social aspect of sustainability.
5. Most studies focus on an analysis at the product level rather than the service or company level, and the industries of focus for these product-level analyses often revolve around aerospace, automotive, prototyping, or tooling.

Using system modeling and analysis tools, this study will attempt to address all the gaps mentioned here. The application of different methods for this study does not mean that some of these gaps could not be addressed with the tools described above.

2.6. System Modeling and Analysis Tools

System methodologies are other examples of holistic, integrative, and quantitative approaches that could help simultaneously assess AM's economic and environmental impacts and fill the gaps highlighted above. These tools rely on system thinking principles that enable the understanding of complex systems. They capture the dynamism and non-linearity in system behaviors, break down multi-stakeholder socio-technical problems, and witness the emergent properties that appear when analyzing all elements of a system and their relationships together rather than individually [130]. Applying such an approach should ensure stakeholder needs are met, value is delivered, and a solution can be integrated easily, evolve flexibly, and operate simply and reliably [130]. Many resources and tools exist, as described in Gannon and Monat's literature review on system thinking [131]. The tools summarized below can be used to explore, understand, and quantitatively inform stakeholders designing, deploying, and managing a strategy, product, process, or organizational structure.

- **Stakeholder Analysis** – Analysis aiming at mapping system stakeholders needs to understand the flow of value among the stakeholders and the system. This exercise connects needs to project goals and clarifies the context around a problem. Many stakeholder analysis techniques exist including value exchange assessment, stakeholder value map, prioritization [132], or stakeholder value network [133]. Using interviews, surveys, and literature reviews is essential to collect all relevant information to perform stakeholder analyses. These tools help define the objectives and priorities of a design effort, but they do not design the system itself.

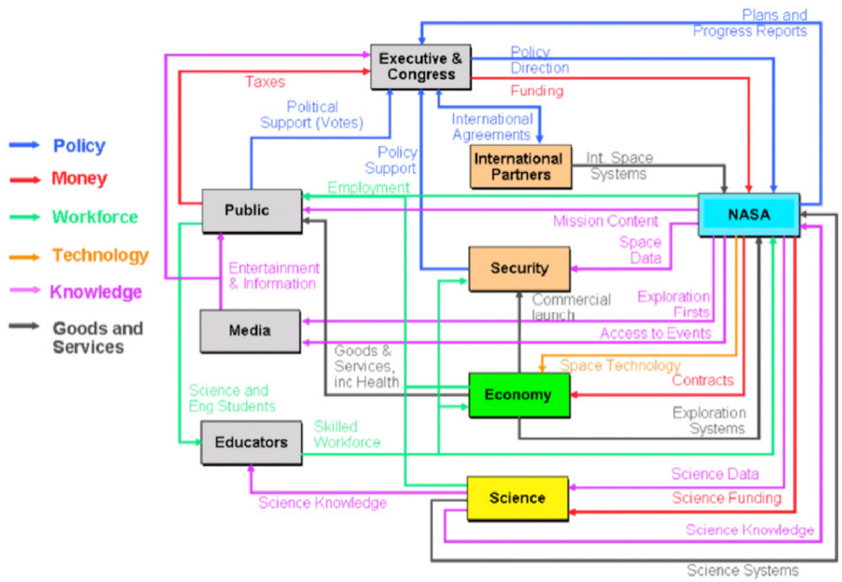

Figure 4. Example of stakeholder value network. Source: https://api.semanticscholar.org/CorpusID:41030296

- **System Decomposition** – Tool consisting of breaking down of a system into its elemental components or constituents. Simple in concept, decompositions can lead to many levels of elements or be somehow arbitrary. This technique aims to structure the organization and relationships between the components of a system to better understand its physical or functional links [130]. This method is useful to manage the complexity of a system and identify more optimal ways to integrate its elements. It is an essential part of architecting a system but does not quantify the value of this system to stakeholders.

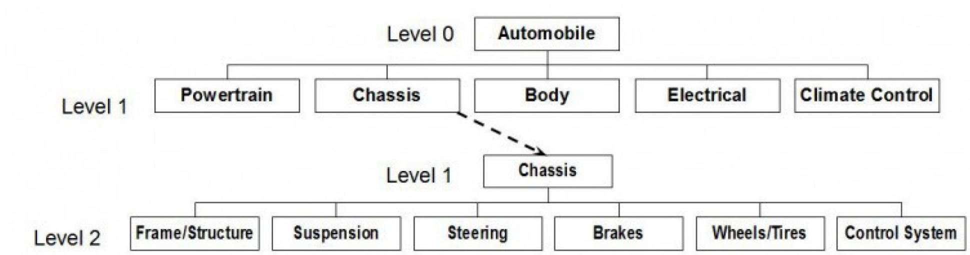

Figure 5. Example of decomposition. Source: https://www.ahlmaneng.com/methods

- **Object-Process Methodology (OPM)** – OPM is a system representation language (conceptual or software-based) mapping objects (people or physical things), processes (verb, action), and the relationships between them to explain the functioning or structure of a system [134]. It can provide explicit representations of complex systems but does not easily allow comparison between various system options. OPCloud and SysML are two model-based system engineering software supporting this type of analysis.

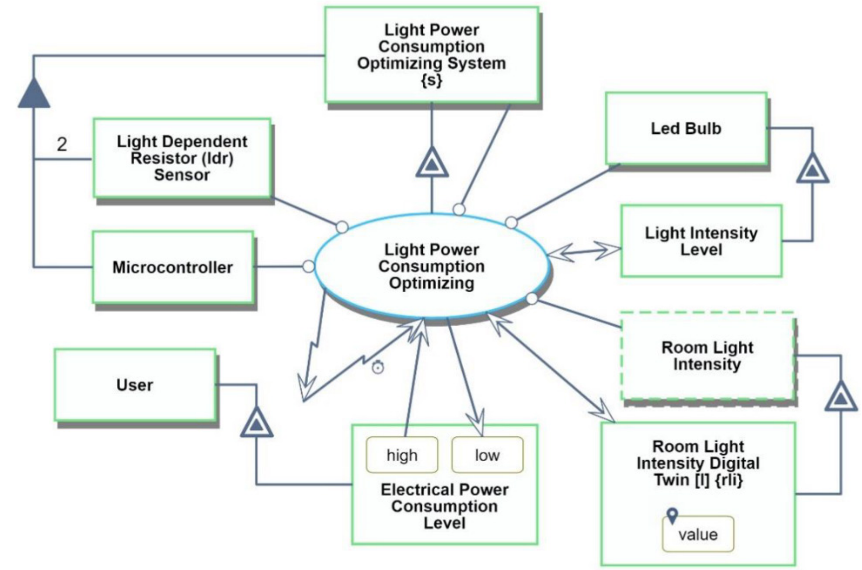

Figure 6. Example of object-process diagram. Source: https://www.mdpi.com/2076-3417/11/5/2301

- **Design Structure Matrix (DSM)** – A term invented by Steward in 1981 [135] and a tool extensively developed by Ulrich and Eppinger [136], DSM is a graphical network modeling method applicable to problems ranging from modularity, system integration, organizational design, to project planning and more. It consists of an n-by-n matrix, often populating the same set of elements in the rows and columns, that can visualize and analyze dependencies between elements. It is a simple and effective tool but can become cumbersome with many elements. However, paired with computational tools, it can provide much quantitative information about the complexity and efficiency of a system [137].

		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
Radiator	A		X														
Engine Fan	B	X				X											
Heater Core	C																X
Heater Hoses	D																
Condenser	E						X		X								
Compressor	F					X			X	X							
Evaporator Case	G																X
Evaporator Core	H					X	X			X							X
Accumulator	I						X		X								
Refrigeration Controls	J																
Air Controls	K																
Sensors	L																
Command Distribution	M																
Actuators	N																
Blower Controls	O																X
Blower Monitor	P			X				X	X							X	

Figure 7. Example of design structure matrix. Source: https://dsmweb.org/different-dsm-types/

- **Tradespace Analysis or Exploration** – A tradespace is a multi-dimensional representation of possible design or architecture alternatives. These alternatives are derived from various combinations of design variables that are already existing or new, enabling the creation of reconfigured or novel designs [138]. Two or more competing dimensions are used to evaluate the options and define the value tradeoffs that each design comes with. A dimension can be an aggregation of multiple attributes leading to a multi-attribute tradespace exploration (MATE) [138]. Once a tradespace is created, the optimal options can be identified using concepts such a pareto frontier and utopia point, or more advanced optimization methods [139]. This tool is meant to provide decision makers a general, but quantifiable guidance on many options rather than a detailed comparison between a few concepts [130].

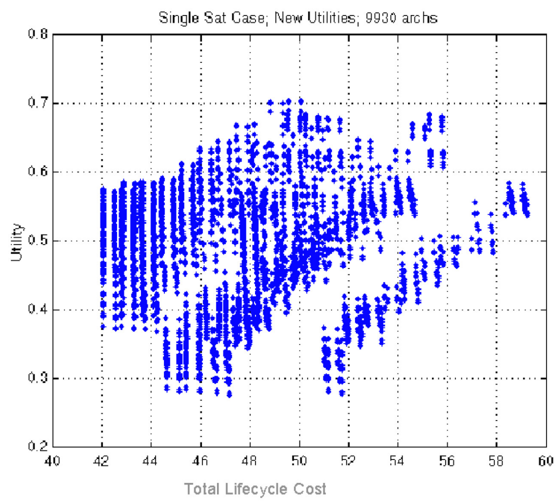

Figure 8. Example of tradespace analysis. Source: https://api.semanticscholar.org/CorpusID:14466551

- **Flexible Design Analysis** – System modeling methodology developed by de Neufville and Scholtes [140]. This approach recognizes uncertainty and adequately plans for it by creating flexible design options. Flexibility minimizes the downsides of uncertainty, maximizes the upsides, and prepares system managers to adapt to future needs proactively. The analysis often integrates other techniques, such as decision rules and Monte Carlo analysis. This method has been used in a variety of projects, such as construction and infrastructure [141], new system design evaluation [142], or complex system deployment [143]. This type of analysis is mostly used to measure a project's financial viability, whether on a profit or cost basis.

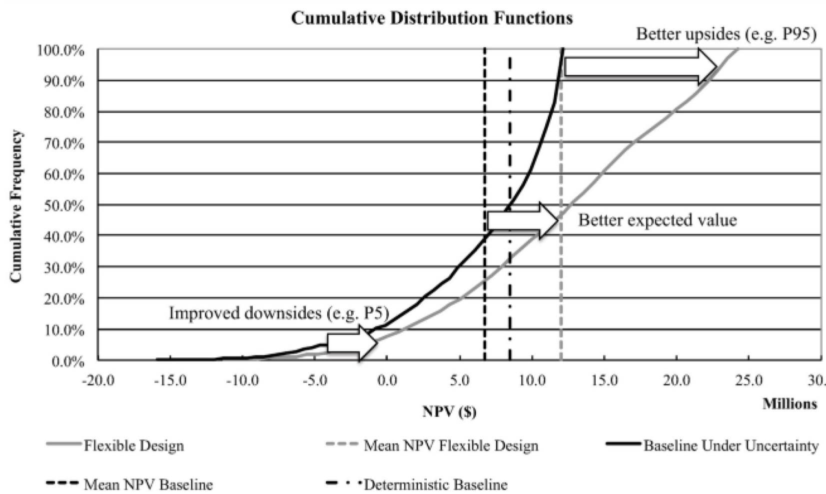

Figure 9. Example of flexible design analysis. Source: https://doi.org/10.1007/978-3-030-46054-9_35-1

- **System Dynamics** – System modeling method based on the theory of feedback control developed in the 1950s by Jay Forrester [144]. In this approach, system components are connected via various interactive relationships such as causal, feedback, or reinforcing loops. Multiple system dynamics modeling tools such as iThink [145], Stella [131], or VenSIM [146] are available and can make this approach quantitative and time-dependent. This tool helps stakeholders understand complex system dynamics and unintended behaviors, leading to more data-driven decision-making.

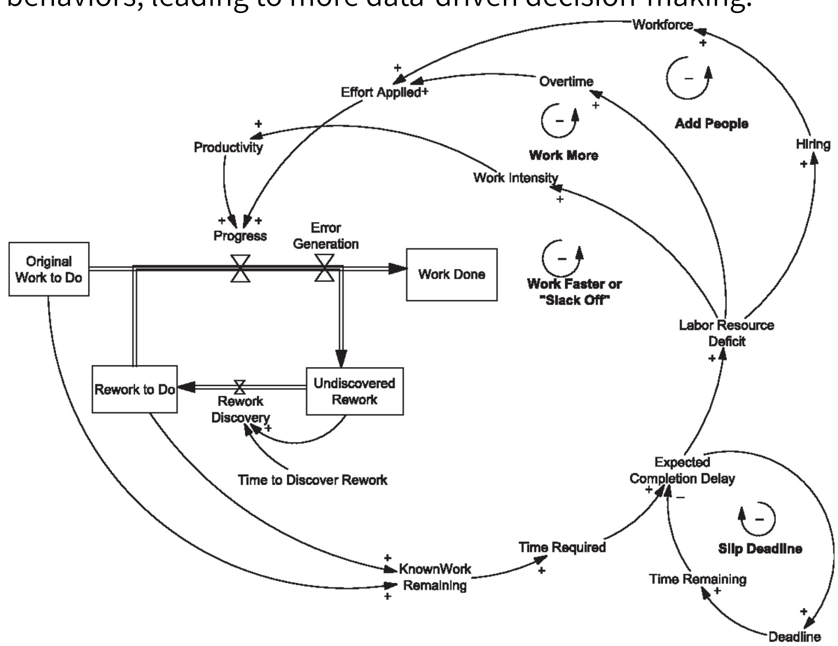

Figure 10. Example of system dynamics model. Source: https://api.semanticscholar.org/CorpusID:18630218

Historically, system methodologies have been applied for performance, quality, and cost purposes, but also for sustainability improvements, notably with the creation of simulation tools such as EnROADS, which uses system dynamics models to assess the impact of various multi-stakeholder climate solutions [147], or the use of DSM to model the coupling between the many domains involved in urban development projects and its impact on the overall sustainability of the system [148]. The objective of this thesis is to take advantage of the multi-dimensional value of these tools to better understand the decision space between financial and environmental considerations. Tradespace analysis and flexible design analysis are the system methodologies employed in the case study presented in this document. These approaches were chosen to fit the case study partner's needs, which focus on understanding high-level trends among many parameters (hence tradespace analysis) and the impact of investment decisions to scale capacity considering the uncertainties around the technology and market (hence flexible design analysis).

3. Case Study: Problem Statement, Objectives and Methodology

3.1. Purpose

The analysis presented in this thesis is built on a single case study about the strategic decisions an internal AM service unit within a large consumer goods company needs to make to grow this new production capability. In this thesis, the term “case study” is loosely drawn from the traditional definition used in social science research. It follows the same principle of boundedness [149] by limiting the study to a specific AM service unit in this current time period. It is also descriptive, explanatory, and exploratory [150] in the sense that this study attempts to describe the environmental and economic tradeoffs in AM, explain the factors affecting AM’s financial and environmental performance, and explore the gaps in the methodologies applied to inform future development work. Beyond this, using the term deviates from the original intent to investigate a phenomenon in a real-life context to test or build a theory [151] by aiming at demonstrating whether an established methodology is effective when applied in an industry-specific, real-life scenario.

In fact, the objective of this study is to evaluate the effectiveness of systems modeling techniques in drawing a robust picture of the tradeoffs between the financial and environmental drivers of AM, ultimately guiding the service unit toward decisions for the sustainable growth of this function. The ability of this introductory analysis to facilitate the adoption of new mental models and tools when evaluating the strategic and operational direction of a business unit, AM-specific or not, will also be assessed.

The novelty and contribution of this work lie in the application of system modeling and analysis tools for AM deployment at the business unit level, considering the diversity of products a consumer goods company offers. To the best of our knowledge, existing research on AM has yet to consider this scale of application or the use of these tools to guide strategic AM decisions.

The case study consists of two major analyses: a tradespace analysis of different product characteristics and lifecycle paths and a flexible design analysis of the opportunities to embed flexibility in AM service investments. For each approach, the developed models leverage a combination of company data, third-party data, and information found in the literature. A summary of the usefulness and limitations of each technique constitutes another piece of this study. Final recommendations stemming from the gaps identified in the approaches are provided as well to guide future developments.

3.2. Case Study Description

3.2.1. AM and the Consumer Goods Industry

The consumer goods industry has seen a shift of AM use from rapid prototyping to end consumer products [21], with the rise of fast-changing customer needs requiring manufacturers to adapt and innovate to stay competitive continuously [12]. This industry greatly benefits from the accelerated time-to-market, innovative design flexibility, and mass customization advantages 3D printing technologies can offer [17]. Using 3D scanning technologies combined with AM, many companies are manufacturing personalized products such as Smith's 3D printed ski goggles or Campfire Audio's custom earbuds [152]. Another reason for adopting AM in the consumer goods sector is sustainability and the ability to use the technology to step closer to circular economies [17]. The German company VAUDE launched the first 3D printed and welded backpack that is fully recyclable due to its single-material design [153].

From a compliance with sustainability goals and targets standpoint, the consumer goods industry represents slightly less than 10% of global emissions [154], which mostly come from the value chain emissions (equivalent to Scope 3, based on the GHG Protocol definition [26]). Scope 3 emissions are sometimes difficult to address for this sector since it consists of influencing downstream and upstream players, including suppliers, retailers (if not the company), and consumers, to improve their practices [155]. At this stage, 151 retail companies such as Ikea, Macy's, Nordstrom, and Home Depot have defined and received approval for their targets and commitments using the Science-Based Target Initiative (SBTi) framework [156].

3.2.2. Introduction to the Case Study Company: Decathlon

Decathlon, a French sporting goods company, is also part of this group that has set science-based targets (SBT) and committed to reaching the 1.5C goal by 2026 and net zero by 2050 [156]. To reach the short-term goal, Decathlon has defined the following targets: (1) reduce scope 1 and 2 emissions by 90% from a 2016 base year, (2) reduce scope 1, 2, and 3 by 53% per value added within the same time frame, and (3) ensure 90% of suppliers by emissions will have SBT by 2026 [157]. In addition to these targets, Decathlon has also set internal objectives to reach by 2026: (1) use of an eco-design approach for 100% of its products and reduce each product's CO2 footprint by 40%, (2) 100% renewable energy sourcing for its stores and warehouses, and at supplier sites, (3) 30% of products need to be qualified as repairable, (4) 100% of retail countries having second-hand product offerings [158]. To dive deeper into the circularity targets, since 2021, Decathlon has established four initiatives that are still in the experimental and implementation phase: (1) develop a repairability framework where a product is called repairable if it is documented, has available spare parts, can be disassembled, and the repair costs are more than 30% lower than the new product price, (2) adopt a recyclability index where each product would be assessed for its recycling potential, its use by an industry sector if recycled, its link with the recycling industry, and the potential quality deterioration of recycling, (3) incentivize a product service system rather than product ownership approach, enabling maximization of the product use before recycling or disposal through buy-back programs, product hires (meaning subscription-based rental), and product repairs in stores or at home [159]. With these efforts, Decathlon has seen circular-economy sales rise in 2022, shifting from the stagnation seen in 2020 and 2021[16].

This push for action was triggered by a 3% increase in the company's absolute emissions between 2016 and 2021 (even though carbon intensity, measured in €/tCO2, decreased by 10%) [158]. The rise in business activity was the cause of this poor absolute environmental performance. In fact, founded in 1976 in Lille (France), Decathlon has grown into one of the largest sporting goods companies in Europe and the world [162], reaching €13.8B in net sales in 2021 [163] and €15.4B in 2022 [164]. With 105,000 employees and 1751 stores spread across 72 countries globally [164], this family- and employee-owned firm has for mission to "move people through the wonders of sport". Known to the public as a large retailer of high-quality and low-price items, Decathlon also designs and manufactures its own products, offering gear for more than 80 sports categorized into 20 brands with their own product development and design capabilities [165]. The company revolves around three main pillars, including a focus on the well-being of its employees, called "teammates", a fundamental strategy centered on innovation, and a responsible commitment to sustainable development [166].

Another driving force for these efforts is Europe's impending regulatory and legal landscape affecting product manufacturers. Stemming from the European Green Deal mentioned in the literature review, in 2022, the European Commission proposed new rules to make products more sustainable in the EU through eco-design and circularity requirements, energy efficiency product labeling, sustainable market development, and consumer empowerment via information transparency and accessibility [167]. As a foresight to these new regulations and in support of the Green Deal, since 2013, the European Commission has been developing the Product Environmental Footprint (PEF) measure to streamline environmental assessment methods and rules across European market players by engaging a diverse set of stakeholders such as brands, NGOs, and LCA service providers [168], [169]. This approach is based on the ISO-approved LCA methodology [80] and, therefore, requires a thorough collection of measurements on all product lifecycle stages from raw material extraction to end-of-life. If primary data (data directly provided by the company or suppliers) is not available, companies have access to the EU's Environmental Footprint (EF) database, created in partnership with data

[16] It is difficult to gauge how all the targets described in this paragraph compare in absolute value to others in the industry given that often absolute values are not shared, and different time frames are considered. It is known, however, that some retailers are ahead by already using 100% renewable energy in their stores since 2019, such as Walmart [160], or by being further along in their transition to 100% renewable electricity such as Nike (93% for Nike vs 85% for Decathlon as of FY22) [161].

developers such as Ecoinvent[17] or Glimpact[18]. For the impact assessment portion of the LCA, the PEF method considers 16 environmental indicators (midpoint categories), which aggregate into a single PEF score, referred to in this thesis as EF single score, forming the impact 'price' of a product. The aggregation is done using weighting and normalization guidelines from the EU and ISO [170] to facilitate communication to stakeholders and balanced decision-making. The indicators considered are the following [168]:

1. Climate change, *in kg CO2 equivalent*
2. Ozone depletion, *in kg CFC-11 equivalent*[19]
3. Human toxicity – cancer, *in CTUh*[20]
4. Human toxicity – non-cancer, *in CTUh*
5. Particulate matter/respiratory inorganics, *in kg PM2.5 equivalent*[21]
6. Ionizing radiation – human health effects, *in kg U^{235} equivalent (to air)*
7. Photochemical ozone formation, *in kg NMVOC*[22]
8. Acidification, *in mol H+ equivalent*
9. Eutrophication – terrestrial, *in mol N equivalent*
10. Eutrophication – fresh water, *in kg P equivalent*
11. Eutrophication – marine, *in kg N equivalent*
12. Ecotoxicity – fresh water, *in CTUe*[23]
13. Land use, *in pt*[24]
14. Water use, *in m^3 world equivalent*
15. Resource use – minerals and metals, *in kg antimony (Sb) equivalent*
16. Resource depletion – fossil, *in MJ*

Decathlon is part of the PEF project and has integrated environmental assessment as a core part of its internal efforts by forming specialists to lead the development of an internal product sustainability database and support design and product engineers in making more informed decisions about what to stop or improve [159]. The sustainability strategy at Decathlon is implemented by informing and guiding its teams through the creation of impact databases and decision tools rather than setting specific targets for each business unit. Moreover, to avoid any more regulatory issues from greenwashing or misleading sustainability labels [172], the French

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[17] More information available at https://ecoinvent.org/activities/environmnetal-footprint-data/ef-3-0-data-provision/
[18] More information available at https://www.glimpact.com/about-glimpact
[19] CFC-11 = trichlorofluoromethane, a chlorofluorocarbon
[20] CTUh = comparative toxic unit for humans
[21] PM2.5 = particulate matter with a diameter of 2.5μm or less
[22] NMVOC = non-methane volatile organic compound
[23] CTUe = comparative toxic unit for ecosystems
[24] pt = "points", dimensionless unit for Soil Quality Index using the LANCA model [171]

company asserts it is ensuring the quality of its initiatives by collaborating with partners such as ADEME[25], a governmental sustainable transition agency, in the use of its repairability index and the development of an environmental textile database, or AFNOR[26], a French certification group, to share research and data for the development of a durability standard [159].

3.2.3. Introduction to the Case Study Partner Team: Add Lab

In this effort to quantify environmental impact and measure progress against the 2016 baseline, in 2022, Decathlon did a greenhouse gas emission inventory of its activities following the GHG Protocol and using the Ecoinvent and Glimpact calculator and database tools, among other estimation methods. The study showed that raw material extraction and product manufacturing accounted for 78% of the company's carbon footprint, as seen in **Figure 11**. This result is not surprising since upstream operations (i.e., raw material extraction and production) are often the largest contributor to emissions across industries [173]. However, as a retailer, the product use phase typically represents a larger percentage of the lifecycle emissions [174], as seen in the clothing industry, for example [175]. This unexpected result might be because Decathlon offers a large variety of items that do not require washing (unlike clothing and apparel) or energy use (unlike electrical equipment), such as bikes, helmets, inflatable kayaks, or fitness equipment.

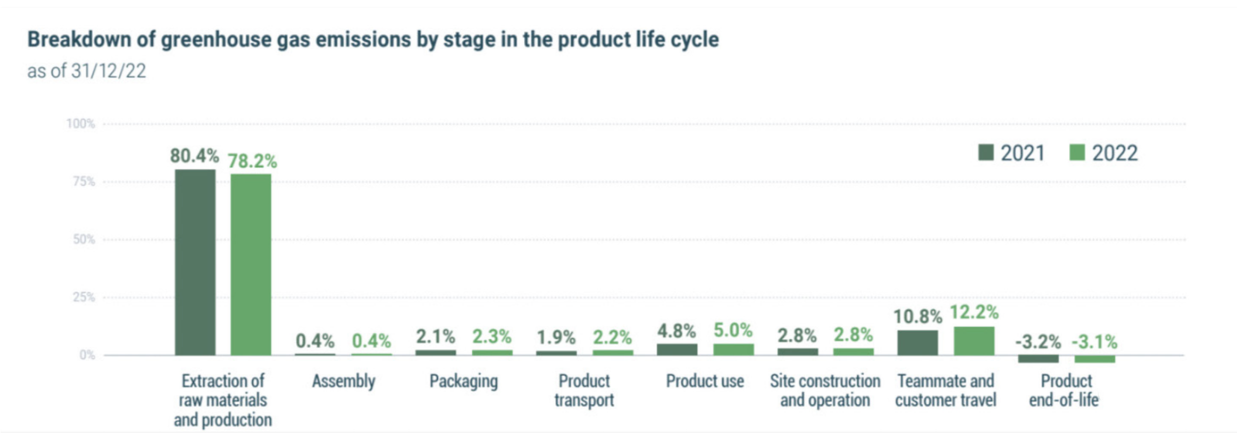

__Figure 11.__ Breakdown of Decathlon's GHG emissions across product lifecycle stages. Sourced from Decathlon's FY22 non-financial report [176].

Pressed by this realization, Decathlon's original investment in the exploration and implementation of innovative manufacturing technologies has gained new traction to improve the environmental impact of its products, increase circularity, and reduce the company's overall GHG emissions. As one of these innovative technologies, additive manufacturing (AM) was introduced at Decathlon in 2016 with the creation of the Add Lab team, a team dedicated to developing 3D printing as a new manufacturing service for the company. Now beyond the proof-

[25] More information available at: https://www.ademe.fr/en/frontpage/
[26] More information available at: https://www.afnor.org/

of-concept stage, the objective of this internal service unit is to demonstrate the value of AM and its potential to produce more eco-friendly products across sport brands and minimize the negative impacts on the planet. While emission and circularity targets specific to the Add Lab are not defined, the tactical approach of the team can be described in two folds: (1) develop reference impact measurements for the technology in compliance with the PEF method and make this available to product designers and engineers during the product development phase, and (2) identify the levers and tools that can be used to further optimize the environmental and financial value of 3D printing and the services Add Lab provides over conventional manufacturing methods. This thesis will focus on effort #2.

3.2.4. An Overview of Add Lab Operations

While experimenting with multiple 3D printing technologies, the Add Lab team owns two HP MultiJet Fusion printers (see **Figure 12**), which are designed for large-scale production but can also support new product development. These machines are operated within a dedicated facility at Decathlon's largest conception center, the B'TWIN village, in Lille. According to the 2023 Wohlers Report, HP's MJF printer is one of the most profitable systems on the market and is the most likely to be purchased by service providers wanting to expand their AM capacity [17]. Tagliaferri et al. also showed in their comparative study between SLS, MJF, and FDM that HP's printer had the fastest payback period and the lowest environmental impact thanks to its lower energy consumption and decent printing speed [129]. Add Lab members also highlighted its desirable ratio of part capacity versus part quality and its user-friendliness, enabling faster workforce training compared to other AM technologies.

Figure 12. *HP Multi Jet Fusion 5200 Industrial Solution.*

HP's 3D printing technology combines elements from both power-bed fusion (PBF) and binder jetting (BJ) processes. It is a powder-bed, layer-by-layer process that uses fusing and detailing agents and heat from infrared to fuse polymer powder particles together and form a final object. For the deposition of its agents, HP leverages its 2D printing inkjet technology. The printing process is followed by multiple post-processing steps, including sandblasting to remove loose powder particles from the surface of the parts, dyeing to add color, and vapor smoothing to create a better surface finish for the part. The general process is shown in **Figure 13**.

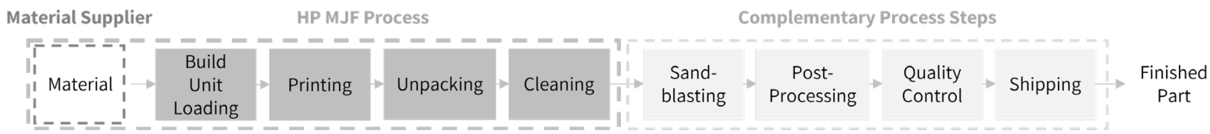

Figure 13. *General additive manufacturing process using HP MJF technology.*

Currently, the Add Lab is a 15-person team operating in a 40 m^2 facility (only considering the space occupied by the machines supporting the 3D printing process). Given the small footprint of the facility limiting the Add Lab capacity, the team leverages local additive manufacturing service bureaus to support any demand that exceeds its in-house capacity, a service on which the Add Lab still drives some revenue. So far, Add Lab has developed its expertise and capabilities to support the demand for three major types of applications:

1. **Prototypes** for product development work done by designers and product engineers across the company. In 2023, the Add Lab produced almost 23,000 prototype parts, a growth of 24% compared to 2022.

2. **Large-scale production parts** going to an assembly facility or directly to a Decathlon retail store for end customers. In 2023, the Add Lab manufactured about 180,000 production parts, an increase of almost 400% compared to 2022.

3. **After-sales repair components** to support end-of-life strategies for old and current products that do not have a solution for the customers (examples shown in **Figure 14**). In 2023, the number of after-sales repair parts 3D-printed was about 3,000, representing a 170% increase compared to 2022.

Figure 14. *Example of after-sales repair parts available in Decathlon's online marketplace.*

The demand for these products is at a growth stage as the personalization, flexibility, and local and on-demand advantages of 3D printing are becoming more valuable for Decathlon sports brands. As the service grows, Add Lab's main priority is to continue supporting new product development through prototyping and meeting the increasing after-sales repair demand. Regarding larger-scale production, the Add Lab will assist and enable the creation of products for mass customization but rely on its growing network of service bureaus to deliver on the production volume as needed.

3.3. Research Questions and Case Study Objectives

Inside or outside of Decathlon, the adoption of additive manufacturing is growing, and its potential for reduced environmental impact and increased circularity is motivating. Ultimately aiming to contribute to Decathlon's strategic goals and support the growing demand for 3D-printed parts within the company, Add Lab is looking for methods to evaluate potential growth strategies that can balance environmental sustainability and financial needs. The following questions are major decisions the team is investigating and wants to weigh against both environmental and financial metrics:

1. For what type of product is AM the right (i.e., more cost-efficient and environmentally friendly) technology to use compared to traditional methods (e.g., what material, production volume, part size, etc.)?
2. In which area should suppliers be incentivized to improve the environmental impact and cost of their products (e.g., materials, hardware)? Is it worth incentivizing through investments such as co-development efforts?
3. Should the Add Lab consider expanding its capacity to support the growing demand in-house or continue leveraging service bureaus to handle any additional demand (as they do today)? Does the location of production matter?
4. Should Add Lab upgrade its facility energy source to meet environmental goals? Is the investment worth the environmental gain?
5. How to better value the use of AM for after-sales repair parts? How can Add Lab continue promoting circularity and repair with the benefits of AM at an attractive cost for the company and the customer?
6. Is metal 3D-printing a technology worth investing in for Add Lab given the potential product portfolio and demand volumes for metal parts? What AM process would be more adequate to use?

The scope of this work is limited to informing decisions 1 through 4 and will leave decisions 5 and 6 for future development work. As hinted earlier, this project leverages the not-yet-validated impact measurement work the Add Lab has accomplished this far and based on this, uses system modeling methodologies to develop decision-making tools that can quantitatively address the questions listed above.

3.4. System Modeling and Analysis Methodologies

To address these research questions, two system modeling and analysis methods are used separately: the tradespace analysis and the flexible design analysis. Before diving into the analysis and the specific objectives of each method in relation to this case study, the general purpose and process to perform each analysis is described in this section. The methods shown below are adaptations from Crawley et al.'s tradespace analysis for system architecture [130] and de Neufville et al.'s approach to flexible design analysis [140].

3.4.1. Method #1: Tradespace Analysis Overview

A tradespace analysis is generally used as a decision-making process in various fields, including engineering, business, and project management. This method aims to explore and evaluate the trade-offs among different decisions and parameters that impact the performance of a system, design, or strategy. The key to assessing trade-offs between decisions lies in evaluating performance metrics that often compete, such as cost and performance, or environmental footprint and cost. This quantitative model helps find a set of options that balance this tension and best deliver on the stakeholders' goals and objectives. This approach is valuable when evaluating complex systems with numerous constraints and dependencies. Visualizing and quantifying the relationships between the variables facilitates informed decision-making. For this case study, this analysis is conducted in eight steps, as shown in **Figure 15**.

Step 1: Defining Objectives & Constraints
The first step of this approach consists of defining the problem statement, the purpose of the analysis, and the system's constraints. When defining the objectives, it is important to clearly state the boundaries of the system to be evaluated, what is included, and what is not. The constraints include any budget limitations, time constraints, technical requirements or incompatibilities, and regulatory requirements.

Step 2: Defining Performance Metrics
The second step of the analysis starts with a good understanding of the stakeholders' needs. From a complete stakeholder analysis, the defined needs can be converted into key system metrics that can be calculated to evaluate performance. These metrics can be direct, such as costs, performance, or environmental footprint, or they can be derived and integrated using a utility function to convert multiple metrics into a single weighted value.

Step 3: Identifying Decisions & Options
The third step involves identifying the various decisions one could make about the system. These decisions can be architectural or design decisions and include variables such as type of

energy consumed, manufacturing process used, functionality targeted, feature size, material used, etc. Each decision will yield multiple options; for example, the manufacturing process could have injection molding, casting, and additive manufacturing as options. Each decision and option should be able to map to the performance metrics established in Step 2.

Step 4: Generating Design Alternatives

The fourth step consists of creating various design or architecture alternatives to compare in the analysis. These alternatives are, in essence, different combinations of decision options. A matrix where each row represents a different possibility can be created. This approach can be done similarly to creating a full factorial for a design of experiment where all possible options are generated, or it can focus only on a subset of possibilities that are of interest to the decision-makers. During this step, it is important to identify the dependencies between decisions to rule out impossible or undesirable combinations. For example, if the design is injection molded, the feature size cannot be smaller than 3mm; therefore, all options using injection molding must exclude options with feature size smaller than 3mm.

Step 5: Establishing Design Vectors

This stage is the first step towards mapping the decision options to the performance metrics identified. It consists in extracting the measurable variables specific to each decision or option that will serve as input parameters for the computation of the model. Uncertainty can be introduced at this stage, where appropriate probabilistic distributions can be fed into the model, instead of using static, deterministic input values.

Step 6: Building the Model

The sixth step consists of building the model using an analytical and simulation tool of choice (e.g., Excel, MATLAB, or Python) to assess the performance of each design alternative against the chosen metrics. The final performance values are calculated directly from the input variables (or distributions) or via intermediate performance parameters stemming from the initial design input vector. Equations should be used to illustrate the dependency between all the variables.

Step 7: Visualizing the Tradespace

This is where the performance of each alternative is visualized into a tradespace diagram. With each axis plotting one of the two performance metrics in tension, the graph illustrates the relationship between different decision and options and their impact on performance.

Step 8: Evaluating Trade-offs & Selecting Options

This final step evaluates the trade-offs between each alternative, decision, and option. Multiple ways exist to parse out the information and extract the value of the analysis. Statistical analyses, color-based representations, or summary tables can be used to assess the sensitivity of each variable against performance or identify and understand trends associated with better or worse performance. Ultimately, these evaluations lead to the identification of optimal alternatives or specific design decisions that best meet or balance the performance objectives.

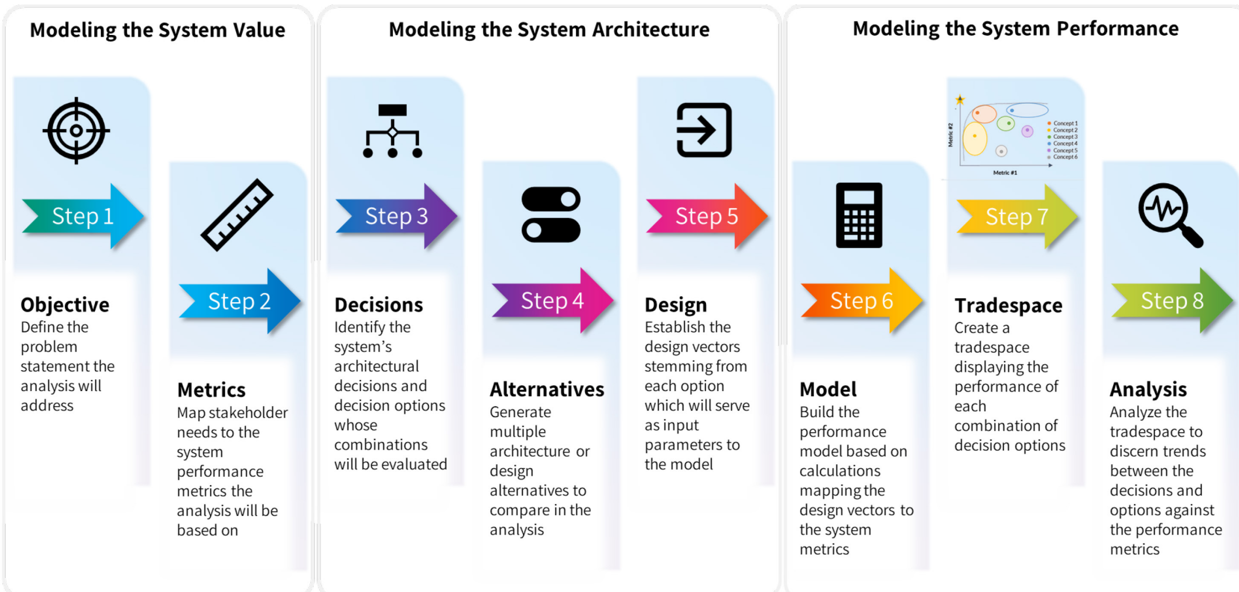

Figure 15. Step-by-step process to perform a tradespace analysis.

3.4.2. Method #2: Flexible Design Analysis Overview

A flexible design analysis is also used as a decision-making process in engineering and management fields. The goal of this method is to generate flexible options for the design of a system, product, or strategy and evaluate the performance of these options against metrics decision-makers care about. Unlike the tradespace analysis, these metrics do not *have to* compete, although they most likely will. This analysis relies on including uncertainty in the model as it aims to use flexibility to maximize the upside opportunities and minimize the downside risks caused by uncertainty. Additionally, a flexible design analysis differs from a tradespace analysis as it considers time as an input for the analysis. This analysis can be performed in eight steps as well, as shown in **Figure 16**.

Step 1: Defining Objective & Constraints

As for the tradespace analysis, the first step of this approach consists of defining the goals of the analysis. The system boundaries and project constraints are also defined at this stage.

Step 2: Defining Performance Metrics

The second step of the analysis also involves mapping the stakeholder needs to key system metrics that can be calculated to evaluate performance. These metrics can be direct or derived and integrated using a utility function. Given that time is a component considered in this approach, it is important to assess if the metrics have a time value, such as costs or revenue, where a discount rate will need to be defined.

Step 3: Identifying the Model Inputs

This stage consists of defining all the input parameters needed to compute the model. These parameters can come from available sources of information (e.g., company data, official databases, market data, etc.), be derived based on a set of variables (e.g., future projections), or can be assumed using best judgment.

Step 4: Inserting Uncertainty

Uncertainty is introduced at this stage, replacing static, deterministic input values with appropriate probabilistic distributions. Given that many parameters can exhibit variability, a sensitivity analysis is performed at this stage to evaluate which uncertainty impacts the system's performance most. Selecting the most sensitive parameters allows for a more realistic representation of the system without overwhelming the analysis.

Step 5: Defining the Model Decisions

Similar to the architectural and design decisions defined in the tradespace analysis step-by-step process, these model decisions consist of choices the decision-makers or system designers have to make at some point throughout the duration of the analysis. The decisions can be technical, strategic, or managerial. Examples include whether to invest in new resources, build infrastructure now or later, or continue or abandon a project.

Step 6: Building the Model

This step consists in building the model over the chosen period, using the defined input parameters, and embedding the decisions of interest. Any analytical and simulation tool can also be used for this modeling work (e.g., Excel, MATLAB, or Python). This step is used to assess the system performance against the chosen metrics in three phases: (1) establish a base case considering the static input variables, (2) compare the impact of uncertainty by treating input parameters as distributions, and (3) compare flexible options defined in Step 7. As for the tradespace analysis, equations should illustrate the dependency between all the variables.

Step 7: Generating Flexible Options

Once the base case without and with uncertainty has been modeled, flexible design options can be generated. This step involves the identification of creative ways of reducing the risks and increasing the opportunities associated with the original design. The intent is to enable designers to adjust to new situations easily and cost-effectively by accounting for the uncertainties of reality and the changing circumstances their design might be subject to. Flexibility can include delaying a decision, building a strong enough foundation to provide to option to build more later, or adopting dynamic pricing strategies to better respond to a market. Options should fit within the constraints of the system and be realistic.

Step 8: Evaluating & Selecting Options

This final step evaluates the trade-offs between the base case and each flexible option based on the system performance metrics. Both target performance curves and summary tables can be used to assess and compare the behavior and outcome of each design. Ultimately, these evaluations lead to the selection of options that are more prone to minimizing risks and maximizing upsides compared to the original design, meeting the needs of stakeholders.

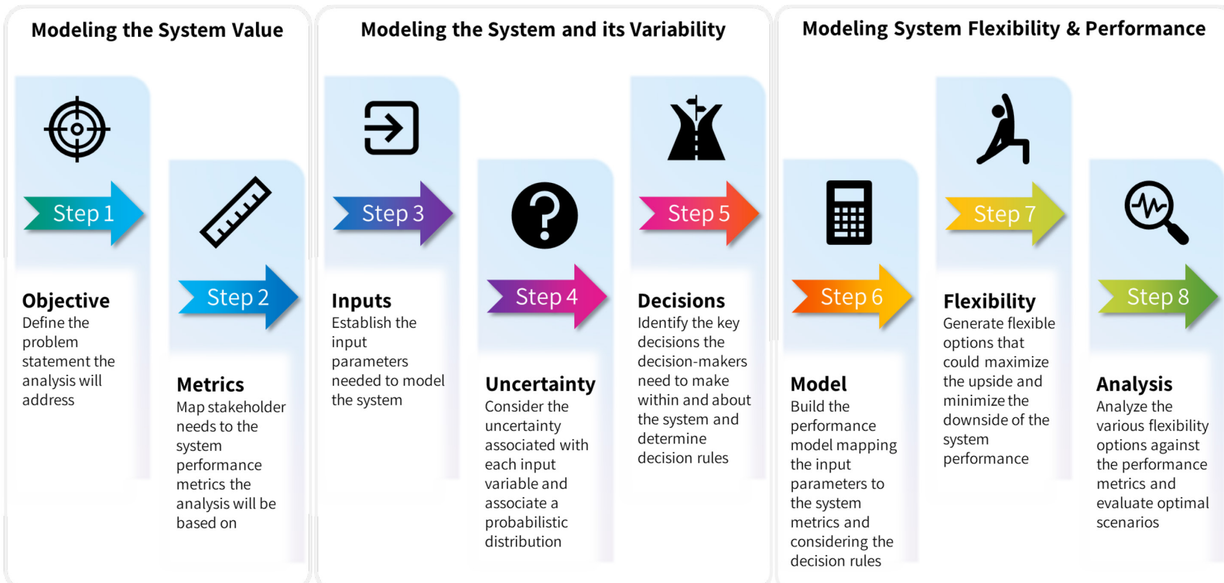

Figure 16. Step-by-step process to perform a flexible design analysis.

3.5. Case Study Disclaimer

The cost and revenue data used to build the case study models are hidden intentionally to preserve the confidentiality of Decathlon's accounting practices. The final performance results are shared since they are not representative of all the services Add Lab provides and should not be interpreted as exact values since some of the parameters used in this analysis were rounded or assumed.

4. Case Study: Product Lifecycle Tradespace Analysis

4.1. Analysis Objective & System Boundaries

*(**Figure 15** process step: Step 1 “Objective”)*

In this case study, the tradespace analysis described in the prior section is used to guide Add Lab in answering the research questions:

- #1: For what type of product is AM the right technology to use compared to traditional methods?
- #2a: In which area should suppliers be incentivized to improve the environmental impact and cost of their products?
- #3b: Does the location of production matter?

The aim is to guide Add Lab towards product types and lifecycle strategies that are more suited for additive manufacturing and provide a general idea of the decisions lowering environmental footprint and reducing costs for the company. In this project, what is meant by “lifecycle strategies” is the series of decisions various stakeholders will need to make along a product’s lifecycle. A product designer will need to select the type of material to use, and the engineer will decide on the manufacturing process needed to achieve design requirements and the most attractive manufacturing location. Then, consumers will purchase this product wherever they are located, use it, and eventually dispose of it by recycling it or throwing it in the trash. Guiding or enforcing a certain path would be a strategy Decathlon could define. In fact, the company has already started by incentivizing reuse and repair through the launch of product services. A second objective lies in highlighting areas of improvement for the 3D printing space to be more competitive against conventional manufacturing. This can help suppliers prioritize development efforts and inform Decathlon on where to place incentives. The analysis will focus on comparing HP Multi Jet Fusion technology versus injection molding (IM) since these methods are the primary manufacturing techniques used for polymer parts at Decathlon. It is in the interest of the Add Lab to define how MJF can offer benefits (in terms of cost and environmental impact) that injection molding cannot achieve and at what expense. As mentioned earlier, Add Lab does not have a specific product cost or environmental footprint to achieve, given the lack of approved reference data, but is interested in understanding the trends generated by the decisions explored in this analysis.

To perform this evaluation, Excel is used to develop a tradespace model of the system (i.e., product characteristics and lifecycle phases) performance based on environmental footprint and cost metrics. The model considers a cradle-to-grave life cycle approach, starting with raw material production and ending with the product’s end-of-life, as shown in **Figure 17**. EF score calculations encompass the entire product lifecycle except the product use phase. It is assumed to be negligible and, therefore, is excluded from the analysis since the types of products manufactured by the Add Lab would not need to be washed (no textiles or apparel are produced) nor powered (no electrical components). Examples of parts would be a seat wheel for a rowing machine or a watch bracelet, as shown on **Figure 14**. For costs, only the raw material production, product production, and product distribution are accounted for since Decathlon incurs costs only in these phases. Note that the scope levels, as defined by the GHG Protocol, are noted as a reference.

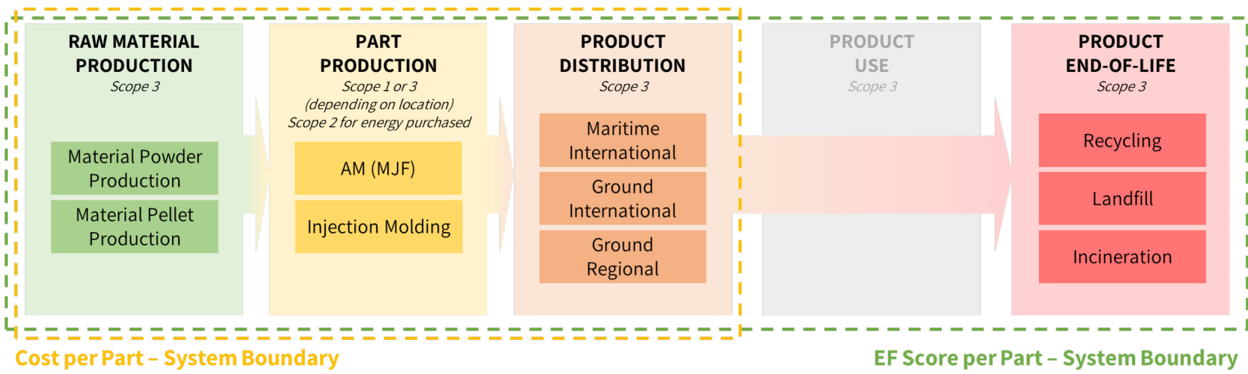

Figure 17. Tradespace analysis life cycle-level system boundary.

Tradespace Analysis Problem Statement:

TO identify which product types and lifecycle pathways offer superior cost-effectiveness and environmentally sustainability through additive manufacturing compared to injection molding

BY evaluating the impact of key product characteristics and lifecycle-related decision options on product cost and EF score

USING an analytical tradespace model representing the operations of Decathlon and Add Lab

4.2. System Model Overview

4.2.1. Model Overview

*(**Figure 15** process steps: Steps 2 "Metrics", 3 "Decisions", and 4 "Alternatives")*

To build the tradespace model and investigate the influence of product characteristics and lifecycle decisions on financial and environmental performance, three key frameworks centered around the lifecycle flow were created in Excel, as shown in **Figure 18**. The first describes the stages the products go through, the decisions that can be made at each stage, and the multiple options each decision is faced with. The second framework consists of the cost model, which stems from the model Add Lab uses to generate unit prices for its customers, a third-party proprietary cost model for injection molding, and literature data. The final and third section relates to the environmental footprint calculations, which follow the PEF methodology the company uses and data from the EF database that was made accessible for this project.

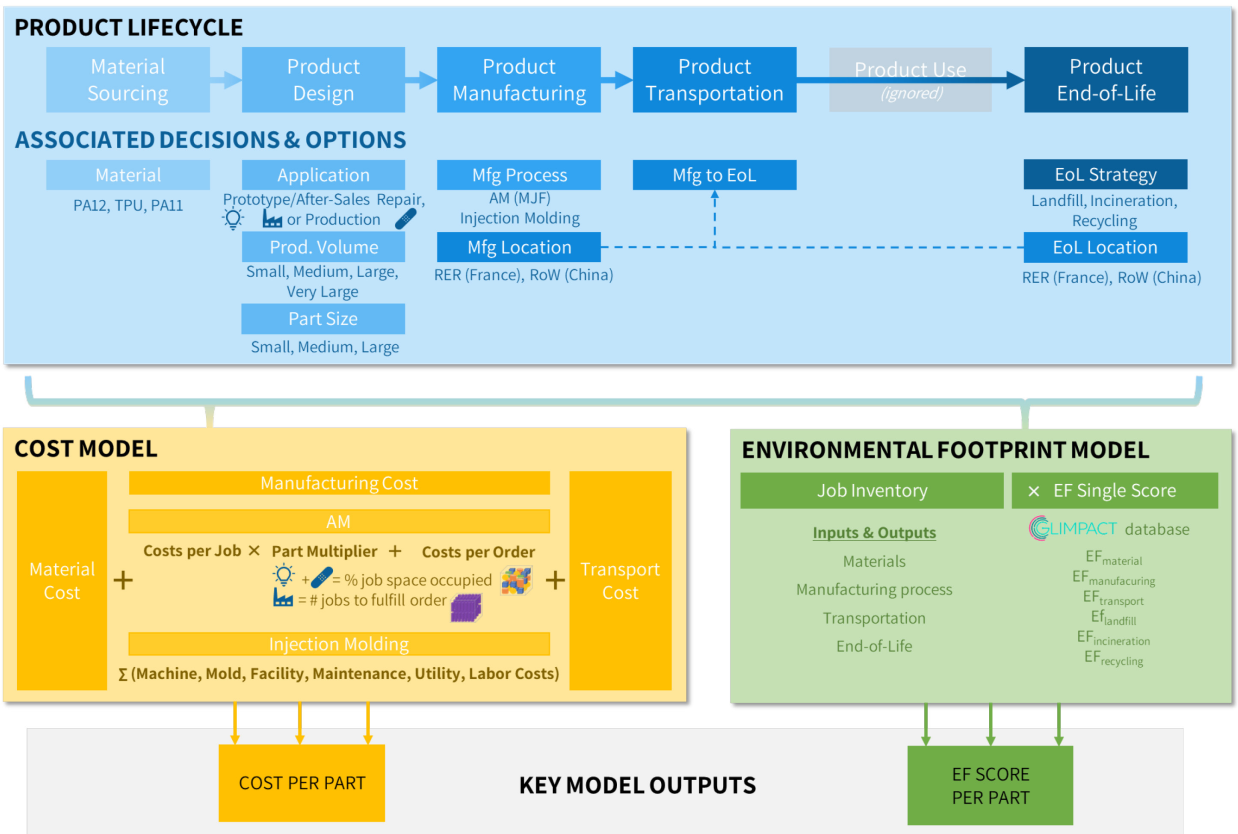

Figure 18. Visual representation of the three key frameworks composing the system model, highlighting the flow between the input variables and the model outputs. The three frameworks include the product lifecycle and characteristics (blue), the costing model (yellow), and the environmental footprint model (green).

The part design improvements that AM could enable are not considered here, leading to a 1-to-1 comparison with injection molding. Moreover, product buyback or repair strategies are not included in the product use phase or end-of-life phase for simplicity and fairness of only comparing one life cycle for all parts' EF and cost metrics. For this same reason, prototype and after-sales repair parts are bundled in the same application group since this decision only affects the type of build configuration that will be used for manufacturing, and these two applications share the same mixed configuration. These three modeling decisions represent an untapped potential for the study, as some of the unique value of AM resides in these capabilities [14].

Different alternatives of product types and lifecycle pathways can be generated based on the decisions and options identified. No design constraints were imposed in this introductory analysis since all alternatives are conceptually possible, and the goal was to understand trends for all decisions. In reality, there might be dependencies and undesirable or impossible combinations, such as between the production volume and manufacturing process if injection molding suppliers do not allow orders of only 20 parts, between repair part applications and injection molding since this technology cannot easily enable this on-demand, low volume process, or between additive manufacturing and manufacturing location since at this stage Add Lab only operates in Europe. Knowing this assumption, all 1728 combinations of product specification and lifecycle path were populated. Among these, six reference alternatives were selected to help ground the study with familiar concepts. The permutation of decision options for each concept is shown in **Table 3**. An average part for each application – prototype, after-sales repair, and production – printed in the Add Lab, and its equivalent injection molded part manufactured in Asia were chosen.

Table 3. *Reference concepts for tradespace analysis.*

REFERENCE CONCEPTS:

Design ID	Concept Name	Application	Production Volume	Part Size	Material	Mfg Process	Transportation	End-of-Life
113	Prototype from Add Lab	Prototype/After-Sales Repair	20	50	TPU	AM (MJF)	RER (FR) - RER (FR)	Recycling
107	Prototype IM Equivalent	Prototype/After-Sales Repair	20	50	TPU	Injection Molding	RoW (CN) - RER (FR)	Recycling
85	After-Sale Repair Part from Add Lab	Prototype/After-Sales Repair	20	50	PA12	AM (MJF)	RER (FR) - RER (FR)	Landfill
79	After-Sale Repair Part IM Equivalent	Prototype/After-Sales Repair	20	50	PA12	Injection Molding	RoW (CN) - RER (FR)	Landfill
1525	Production Part from Add Lab	Production Part	10000	5	PA12	AM (MJF)	RER (FR) - RER (FR)	Landfill
1519	Production Part IM Equivalent	Production Part	10000	5	PA12	Injection Molding	RoW (CN) - RER (FR)	Landfill

4.2.2. Input Parameters from Available Information

*(**Figure 15** process step: Step 5 "Design")*

Most of the input variables present on **Figure 18** either stem from data provided by Decathlon or obtained from a proprietary third-party injection molding cost calculator. The data from Decathlon was given through access to the Add Lab costing model, the latest environmental impact calculations performed on the additive manufacturing process, and access to the EF database. The proprietary injection molding cost calculator was developed by John Busch in 1987 as part of his MIT doctoral thesis [177]. The machine, labor, energy, and facility costs were updated to match current rates. However, the remainder of the parameters were kept intact, assuming the general factors affecting cycle time should have stayed mostly the same. This assumption and method should be verified based on Decathlon's internal data, which were not available at the time of this thesis. Another portion of the values was estimated based on general market trends or best educated guesses. In the tables below, the options for each decision are listed in the first column and represent the model variable parameters. The other columns present all the parameters and values associated with the options. An explanation of the information sourcing is provided for each.

The main data included in the first decision "application" is the additive manufacturing build configuration consisting of mixed and uniform builds.

Table 4. Input parameters for decision 1, application.

Decision #1: Application	AM Build Configuration
Prototypes/After-Sales Repairs	Mixed build
Production Parts	Uniform build

As shown in **Figure 19**, mixed builds are defined as jobs composed of multiple types of parts with varying geometries and sizes, while uniform builds are described as jobs filled with a single type of part design. Prototypes and after-sales repair parts are placed in mixed jobs due to low and irregular production volume, while production parts are only printed in uniform builds since these runs are often large and requested at once.

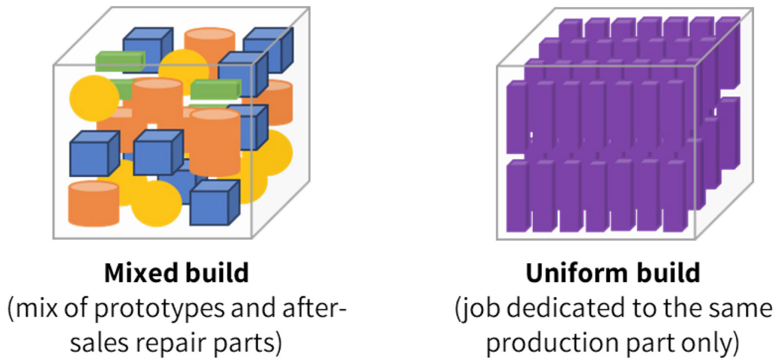

Figure 19. Visualization of a "mixed" build and a "uniform" build.

The input parameters used for the second and third decisions, "production volume" and "part size", represent a categorized range of values encountered in the Add Lab. The production volume represents the quantity of parts (all applications included) produced in one batch. The service unit sees volumes ranging from one part to thousands of parts. The part sizes vary between 1 gram to more than 150 grams. As the demand and types of 3D-printed products evolves, these values could be easily adapted. **Table 5** highlights the values chosen.

Table 5. Input parameters for decisions 2 and 3, production volume and part size.

Decision #2: Production Volume	Number of Parts per Order
Small	20 parts/order
Medium	100 parts/order
Large	1,000 parts/order
Very Large	10,000 parts/order
Decision #3: Part Size	**Part Weight**
Small	5 g
Medium	50 g
Large	100 g

Regarding the material options, it is important to describe why PA12, TPU, and PA11 were chosen and how they differ before diving into the input parameters used. Polyamide 12 (PA12), or nylon 12, is a synthetic high-performance thermoplastic with excellent mechanical properties, durability, and chemical resistance. PA12 has the lowest melting temperature of the various polyamide materials (e.g. PA11). This material can also be reinforced with glass fibers or beads for added mechanical strength, as offered by HP [178]. Add Lab applications made with PA12 include wheels for the seat of stationary rowing machines or adjustable screws for ping pong tables. On the other hand, thermoplastic polyurethane (TPU) is a flexible, lightweight, and durable polymer with good elasticity, abrasion resistance, and chemical versatility. Examples of after-sales repair products printed by the Add Lab with TPU comprise watch bracelets and net tighteners for ping pong tables. Finally, polyamide 11 (PA11) is also a thermoplastic with high chemical resistance and mechanical strength, but it differs from PA12 due to its natural attributes: it is bio-based (i.e., often derived from castor beans) rather than petrochemically sourced. The PA11 material offered by HP and its material supplier has higher reusability, meaning that more unprinted, used powder can be recycled for future print jobs. Add Lab has not produced application parts with this material yet but has added it to its material portfolio for the incoming year, hence the consideration for this study. Images of the PA12 and TPU products are shown in **Figure 20**.

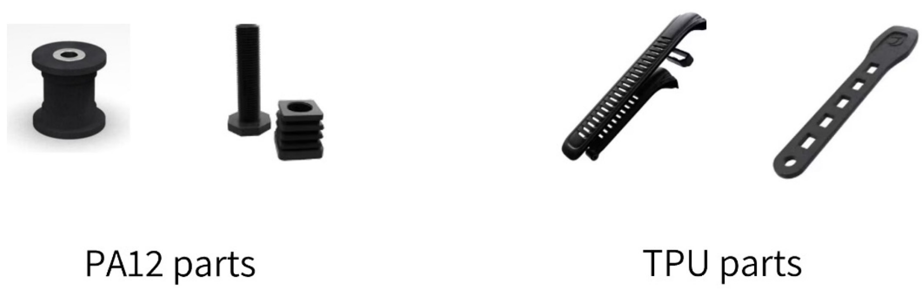

Figure 20. *Example PA12 and TPU after-sales repair parts available on Decathlon online marketplace.*

These materials are very common for additive manufacturing and can also be used in injection molding, though possibly less often. This could impact some of the cost and environment footprint performance since other more commonly used injection molding materials, such as acrylonitrile butadiene styrene (ABS), or acrylic (PMMA) would have been prioritized for further cost and EF reduction efforts over the materials studied here.

Regarding the material input parameters shown in **Table 6**, the material powder costs, densities, powder loss, and environmental footprint scores for the material pellet were provided by Decathlon. Note that the material powder costs are generally an order of magnitude more expensive than material pellet costs. Only some of the 16 EF criteria were available for the latest material powders at the time of this study, preventing the calculation of a single score. These values were, therefore, estimated based on past data. Decathlon provided the material pellet costs for PA12 and TPU and an estimation for PA11. The injection molding cooling time was estimated based on each material's thermal properties using cooling time coefficients extracted from a proprietary, third-party injection molding costing tool.

Table 6. Input parameters for decision 4, material.

Decision #4: Material	Material Powder Cost	EF of Material Powder	Material Powder Density	Material Fused Density
PA12	€/kg	800 dml/kg	0.425 kg/L	1.01 kg/L
TPU	€/kg	507 dml/kg	0.5 kg/L	1.00 kg/L
PA11	€/kg	891 dml/kg	0.48 kg/L	1.05 kg/L
Decision #4: Material	**Material Powder Loss**	**Material Pellet Cost**	**EF of Material Pellet**	**Injection Cooling Time**
PA12	20%	3.70 €/kg	802 dml/kg	4.5 sec
TPU	20%	5.50 €/kg	868 dml/kg	4 sec
PA11	15%	6.00 €/kg	1183 dml/kg	7.5 sec

The fifth decision, "manufacturing process", is the decision with the most input variables as it drives a large portion of the costs and environmental footprint scores, as shown in **Table 7**. Once again, the majority of the data relating to additive manufacturing (cost and EF) and the other EF scores stem from Decathlon and its access to the EF databases. Some assumptions were made for the EF score of 3D printing agents since, as for the material powders, environmental measurements were not available. For the injection molding cost parameters, the third-party calculator tool was used to derive the key input variables to compute the cost per injection molded part. These parameters include, for example, the cycle time coefficients and the mold cost factors and exponents. The cost of the injection molding machine was based on the price of a 2021 Milacron Fanuc Roboshot α-S130iB all-electric and the weight of the injection mold was assumed to be 400kg for all parts. Both values were found in Kazmer et al.'s study [124]. Steel was selected as the mold material, and the mold life expectancy was set at 10,000 parts (value provided by Decathlon). This assumption should be reassessed in future work as proper mold size and lifespan estimation methods could yield different results, especially with the growing trend of using 3D printed mold for smaller production runs [179].

Beyond the variables strictly depending on the type of manufacturing process chosen, there is a set of AM-specific cost parameters that also depend on the type of build configuration used and, therefore, the type of application produced, as listed in **Table 8**. The use of these parameters to compute the final cost per part will be shown in the equations described in the next section.

Lastly, in **Table 7**, the "EF score of process" parameters are colored in orange because they depend on the transportation decision as well. The AM process' EF score is calculated based on the inventory of inputs and outputs tied to the AM process rather than a single value from the EF database since a lifecycle measurement was performed by the Add Lab team, hence the "NA" in the table. Since the detailed lifecycle data is unavailable for injection molding, a single, aggregated value from the database was used.

Table 7. Input parameters for decision 5, manufacturing process.

Decision #5: Manufacturing Process	Process Yield	Electricity Consump.	Facility Footprint	EF of Process (RER – France)
AM (MJF)	93%	128 kWh/job	40 m2	NA
Injection Molding (IM)	94%	22.1 kW	40 m2	40.3 dml/kg
Decision #5: Manufacturing Process	**EF of Process (RoW – China)**	**Daily Printer Capacity**	**Build Volume**	**Packing Density**
AM (MJF)	NA	1.5 jobs/printer/day	59,850 cm3	7%
Injection Molding (IM)	118 dml/kg	NA	NA	NA
Decision #5: Manufacturing Process	**Percent Material Waste**	**EF of Plastic recycling**	**EF of Plastic land/inc.**	**Cost of Agent**
AM (MJF)	25% of printed mass	-350 dml/kg	-1.79 dml/kg	€/kg material
Injection Molding (IM)	NA	NA	NA	NA
Decision #5: Manufacturing Process	**Agent Consumption**	**EF of Agent**	**Sandblasting Waste**	**EF of Glass**
AM (MJF)	0.12 kg/job	500 dml/kg	0.225 kg/job	85 dml/kg
Injection Molding (IM)	NA	NA	NA	NA
Decision #5: Manufacturing Process	**EF of Glass landfill/inc.**	**Compressed Air Cons.**	**EF of Compressed Air**	**Daily Printing Cost**
AM (MJF)	8.5 dml/kg	500 kg/job	0.3 dml/kg	€/day
Injection Molding (IM)	NA	NA	NA	NA
Decision #5: Manufacturing Process	**Manual Unpack Cost per Job**	**Daily Sandblast Cost**	**Sandblast Cost per Job**	**Dyeing Cost per Job**
AM (MJF)	€/job	€/day	€/job	€/job
Injection Molding (IM)	NA	NA	NA	NA
Decision #5: Manufacturing Process	**Vapor Smoothing Cost per Job**	**Shipping Cost**	**Number of Cavities**	**Cycle Time (CT) Constant**
AM (MJF)	€/job	€/production volume	NA	NA
Injection Molding (IM)	NA	NA	1 cavity	10 sec
Decision #5: Manufacturing Process	**CT Cooling Coef**	**CT Weight-Cav Coef.**	**Machine Cost**	**Machine Downtime**
AM (MJF)	NA	NA	NA	NA
Injection Molding (IM)	1.35 sec/sec	0.0151 sec/g/cav	31,250 €/yr	20%
Decision #5: Manufacturing Process	**Maintenance Cost**	**Complexity Exponent**	**Weight Exponent**	**Multi-Cav Exponent**
AM (MJF)	NA	NA	NA	NA
Injection Molding (IM)	5%	2100	0.45	0.4
Decision #5: Manufacturing Process	**Mold Life Expectancy**	**Mass Used for Mold**	**EF of Mold Material**	**EF of Mold Machining**
AM (MJF)	NA	NA	NA	NA
Injection Molding (IM)	10,000 parts	400 kg	205 dml/kg	17 dml/kg

Table 8. Input parameters dependent on decision 1, application, and decision 5, manufacturing process.

Decision #1: Application	AM Build Configuration	Average Parts per Job	Average Part Volume	Software Cost
Prototypes/After-Sales Repairs	Mixed build	36 parts/job	35 cm3	€/production volume
Production Parts	Uniform build	NA	NA	€/production volume
Decision #1: Application	**Daily Dyeing Cost**	**Dyeing Machine Cost**	**Daily Vapor Smoothing Cost**	**Vapor Machine Cost**
Prototypes	€/day	€/production volume	€/day	€/production volume
Production Parts	€/day	€/production volume	€/day	€/production volume
Decision #1: Application	**Finishing Cost**	**Daily Quality Control Cost**	**Labor Hours per Job**	
Prototypes	€/production volume	€/day	3 hrs/job	
Production Parts	€/production volume	€/day	6 hrs/job	

The sixth decision relates to the transportation between the manufacturing and the use locations. The options were narrowed down to two locations: (1) Europe (RER), using France (FR) more precisely, and (2) the Rest of the World (RoW), using China (CN) more specifically. This down-selection was made because China represents the second-largest market in terms of stores for Decathlon [180], France being the first. Add Lab is considering expanding its service availability geographically by setting up a facility in China since the team aims to offer local manufacturing capabilities. The input parameters highlight the cost and environmental impact differences between the two geographies. The costs for France were rounded based on data given by Decathlon, and it was assumed that the operator wage in China was 10% of the French value [181], the electricity cost was 0.079 €/kWh [182], and the facility cost was 20% of the French yearly renting cost [183]. Maritime international transportation costs were derived from the World Container Index [184] and estimated using best guesses for the ground transportation modes. The transportation distances were provided by Decathlon as gross estimations and verified through Google Maps, assuming the European port used would be Rotterdam's and the Chinese one Shanghai's. All the EF score values were extracted from the EF database, except for the regional ground transportation data in China, which wasn't available (the same impact was used for both regions). Only sea and ground transportation are considered since Decathlon has been working on reducing air freight to less than 1% of its products' transport [185].

Table 9. *Input parameters for decision 6, transportation.*

Decision #6: Transportation	Manufacturing Location	EoL Location	Labor Cost	Electricity Cost
RER (France) – RER (France)	RER	RER	25 €/hr	0.09 €/kWh
RER (France) – RoW (China)	RER	RoW	25 €/hr	0.09 €/kWh
RoW (China) – RER (France)	RoW	RER	2.5 €/hr	0.079 €/kWh
RoW (China) – RoW (China)	RoW	RoW	2.5 €/hr	0.079 €/kWh
Decision #6: Transportation	**EF of Electricity**	**Facility Cost**	**Distance Sea Freight**	**Cost of Sea Freight**
RER (France) – RER (France)	25 dml/kWh	300 €/m2/yr	0 km	0.00013 €/tonkm
RER (France) – RoW (China)	25 dml/kWh	300 €/m2/yr	20,000 km	0.00013 €/tonkm
RoW (China) – RER (France)	130 dml/kWh	60 €/m2/yr	20,000 km	0.003 €/tonkm
RoW (China) – RoW (China)	130 dml/kWh	60 €/m2/yr	0 km	0.003 €/tonkm
Decision #6: Transportation	**EF of Sea Freight**	**Distance Intl Ground**	**Cost of Intl Ground**	**EF of Intl Ground**
RER (France) – RER (France)	1.31 dml/tonkm	0 km	5.00 €/tonkm	9.83dml/tonkm
RER (France) – RoW (China)	1.31 dml/tonkm	1000 km	5.00 €/tonkm	11.3 dml/tonkm
RoW (China) – RER (France)	1.31 dml/tonkm	1000 km	5.00 €/tonkm	9.83 dml/tonkm
RoW (China) – RoW (China)	1.31 dml/tonkm	0 km	5.00 €/tonkm	11.3 dml/tonkm
Decision #6: Transportation	**Distance Regional Ground**	**Cost of Regional Ground**	**EF of Regional Ground**	
RER (France) – RER (France)	1000 km	2.00 €/tonkm	220 dml/tonkm	
RER (France) – RoW (China)	1000 km	1.00 €/tonkm	220 dml/tonkm	
RoW (China) – RER (France)	1000 km	2.00 €/tonkm	220 dml/tonkm	
RoW (China) – RoW (China)	1000 km	1.00 €/tonkm	220 dml/tonkm	

Finally, the data for the seventh decision, the end-of-life strategy, solely relates to the environmental impact of each strategy considered in this analysis – landfill, incineration, and recycling – for each location – France and China. Each value was retrieved from the EF database accessed via Decathlon. As mentioned, the cost of these product lifecycle phases was not accounted for since Decathlon does not own the disposal process of its product, and the case study is focused on recommending internal strategic actions.

Table 10. *Input parameters for decision 7, end-of-life.*

Decision #7: End-of-Life	EF End-of-Life (RER – France)	EF End-of-Life (RoW – China)
Landfill	3.5 dml/kg	3.5 dml/kg
Incineration	-9.5 dml/kg	-81.5 dml/kg
Recycling	10.3 dml/kg	43.7 dml/kg

4.2.3. Model Equations for Costs and Environmental Footprint

*(**Figure 15** process step: Step 6 “Model”)*

With all the input parameters defined, the computation of the total cost per part and EF score per part metrics can be mapped. **Equation 1** is the set of equations regrouping the cost calculations, and **Equation 2** summarizes the EF calculations.

The cost per part metric is broken down into three main cost centers – material, manufacturing, and distribution – and normalized based on the production volume. The material cost is influenced by the manufacturing process but follows a similar framework across both processes. It involves multiplying the production volume by the part weight and the material cost per kilogram. A few key differences are the inclusion of the printing agents (fusing and detailing agents) and the refresh rate of material, also named material loss per job, in the AM calculations, while injection molding only considers the material used.

The manufacturing cost drastically differs between the two processes, given that the nature of their operational steps varies widely. On the one hand, injection molding comprises machine, mold, facility, maintenance, labor, and utility costs. The cost equations were derived from the proprietary third-party calculator mentioned in the description of the input variables. They are mostly driven by the cycle time needed to injection mold a single part, as this parameter dictates the utilization metric in all the cost factors. On the other hand, additive manufacturing includes software, printing, unpacking, sandblasting, post-processing, quality control, and shipping costs. They are separated into fixed costs (set per production volume) and variable costs (scaled by a factor specific to the type of jobs printed, either mixed or uniform), as shown in **Figure 19**. For production parts, since all the jobs to complete the order will be uniform, the total number of jobs to complete the order is used to scale the costs. For prototype and repair parts, since one print job is composed of several parts of different geometries, the variable costs are multiplied by the percent space occupied by the order based on what an average “mixed” job looks like. As seen in the input variable table for decision 1 (**Table 8**), some costs, called “daily” costs, must be divided by the daily printer capacity to be scaled appropriately as a variable cost per job. These equations were derived and simplified from the costing model provided by the Add Lab team.

The distribution cost consists of multiplying the production volume and part weight by the distance traveled and the cost of transportation for each means of transportation used.

Across materials, processes, and distribution modes, note that only the electricity, labor, facility, and transportation costs depend on the location. This may present a limitation, as other expenses, such as material or machine costs, may differ if purchased locally or not.

Equation 1. *Set of cost equations leading to final cost per part.*

COST PER PART

$$\boldsymbol{COST\ per\ PART} = (material\ cost + manufacturing\ cost + distribution\ cost) \div production\ volume$$

COST OF MATERIAL

Injection Molding:

$$\boldsymbol{MATERIAL\ COST} = production\ volume \times part\ weight(kg) \times material\ pellet\ cost\ (\frac{€}{kg})$$

Additive Manufacturing (HP MJF):

$$\boldsymbol{MATERIAL\ COST} = production\ volume \times part\ weight\ (kg) \times (1 + material\ loss\ per\ job\ (\%)) \times (material\ powder\ cost(\frac{€}{kg}) + cost\ of\ agent\ consumed\ by\ 1kg\ of\ mtrl(\frac{€}{kg}))$$

COST OF MANUFACTURING

Injection Molding:

$$\boldsymbol{MANUFACTURING\ COST} = machine\ cost + mold\ cost + facility\ cost + maintenance\ cost + utility\ cost + labor\ cost$$

$$\boldsymbol{cycle\ time} = cycle\ time\ (CT)\ constant\ (sec) + CT\ cooling\ coef.(sec/sec) x\ cooling\ time\ (sec) + CT\ weight - cav\ coef.(sec/g/cav)\ x\ part\ weight\ (g)\ x\ \#\ of\ cavities$$

$$\boldsymbol{MACHINE\ COST} = machine\ utilization\ (\%)\ x\ yearly\ machine\ cost\ (€/yr)$$

$$\boldsymbol{machine\ utilization} = (production\ volume\ (parts)\ x\ cycle\ time\ (hr) \div \#\ of\ cavities)/(250\ working\ days\ x\ 24\ hrs\ operations\ per\ day\ x\ (1 - downtime\ (\%)))$$

$$\boldsymbol{MOLD\ COST} = mold\ utilization\ (\%)\ x\ mold\ complexity\ coefficient\ x\ part\ weight\ (g)^{weight\ factor\ exponent}\ x\ \#\ of\ cavities^{multi-cavitiy\ factor\ exponent}$$

$$\boldsymbol{mold\ utilization} = production\ volume\ (parts) \div mold\ life\ expectancy\ (parts)$$

$$\boldsymbol{FACILITY\ COST} = facility\ utilization\ (\%)\ x\ facility\ footprint\ (m2)\ x\ yearly\ facility\ cost\ per\ m2\ (€/m2/yr)$$

$$\boldsymbol{facility\ utilization} = (production\ volume\ (parts)\ x\ cycle\ time\ (hr) \div \#\ of\ cavities)/(250\ working\ days\ x\ 24\ hrs\ operations\ per\ day)$$

$$\boldsymbol{MAINTENANCE\ COST} = investment\ maintenance\ cost\ (\%)\ x\ [machine\ cost + mold\ cost + facility\ cost]$$ --- *facility cost dependent on location*

$$\boldsymbol{UTILITY\ COST} = electricity\ price\ (€/kWh)\ x\ electricity\ consumption\ (kW)\ x\ cycle\ time\ (hr)$$ --- *utility cost dependent on location*

$$\boldsymbol{LABOR\ COST} = labor\ cost\ (€/hr)\ x\ cycle\ time\ (hr) \div \#\ of\ cavities \div (1 - downtime\ (\%))$$ --- *labor cost dependent on location*

Additive Manufacturing (HP MJF):

$$\boldsymbol{MANUFACTURING\ COST\ for\ PROTOTYPE/REPAIR} = fixed\ costs + \%\ space\ occupied\ by\ order \times variable\ costs$$

$$\boldsymbol{Fixed\ costs} = software\ cost + finishing\ cost + shipping\ cost + dyeing\ machine\ cost + vapor\ smoothing\ machine\ cost$$

$$\%\ \boldsymbol{space\ occupied\ by\ order} = (production\ volume \times part\ volume) \div (avg\ part\ volume \times avg\ qty\ of\ parts\ per\ job)$$

$$\boldsymbol{Variable\ costs} = printing\ costs + unpack\ costs + sandblasting\ costs + dyeing\ costs + vapor\ smoothing\ costs + facility\ costs + electricity\ costs + labor\ costs$$

--- *facility, electricity, and labor cost dependent on location*

In general, across fixed and variable costs, if $\boldsymbol{daily}$ costs, costs are divided by $\boldsymbol{daily\ printer\ capacity\ (jobs/printer/day)}$

$$\boldsymbol{MANUFACTURING\ COST\ for\ PRODUCTION} = fixed\ costs + qty\ of\ jobs\ to\ fulfill\ order \times variable\ cost$$

$$\boldsymbol{Fixed\ costs} = software\ cost + shipping\ cost$$

$$\boldsymbol{Qty\ of\ jobs\ to\ fulfill\ order} = (production\ volume \div ROUNDUP((build\ unit\ volume \times material\ density \times packing\ density) \div part\ weight)$$

$$\boldsymbol{Variable\ costs} = printing\ costs + unpack\ costs + sandblasting\ costs + dyeing\ costs + vap.sm.costs + qual.control\ costs + facility\ costs + elec.costs + labor\ costs$$

--- *facility, electricity, and labor cost dependent on location*

In general, across fixed and variable costs, if $\boldsymbol{daily}$ costs, costs are divided by $\boldsymbol{daily\ printer\ capacity\ (jobs/printer/day)}$

COST OF DISTRIBUTION

$$\boldsymbol{COST\ for\ DISTRIBUTION} = production\ volume \times part\ weight\ (tons) \times \begin{bmatrix} international\ maritime\ transportation\ distance\ (km) \times transport\ cost\ (€/tonkm) \\ +international\ ground\ transportation\ distance\ (km) \times transport\ cost\ (€/tonkm) \\ +regional\ ground\ transportation\ distance\ (km) \times transport\ cost\ (€/tonkm) \end{bmatrix}$$

--- *transportation cost dependent on location and mode*

The EF score per part is broken down into five main cost centers, - material, manufacturing, mold, distribution, and end-of-life – and also normalized over the production volume.

The material environmental footprint calculation is straightforward with the multiplication of production volume and the part weight by the EF single score of either the material powder production for AM or the material pellet production for IM.

Regarding the manufacturing process impact, collaborating with the Add Lab at Decathlon provided rich information on the life cycle assessment of the AM process, even though the work is still in progress and the results have yet to be approved. A schematic showing the input and output materials, consumables, energy, and compressed air is shown in **Figure 21**. While counted in the cost calculations, everything greyed out here is not accounted for in the environmental assessment, as data on their production process is not yet available. Until this data is accessible, the AM measurement values cannot be validated and treated as absolute and accurate in this study. The relative trends should still be insightful and informative, however. The functional unit for these impact calculations is 1 kilogram of printed material, allowing for easy computation by product designers or engineers once a final EF score is attributed to this manufacturing process. Based on the material allocation rule, the following is accounted in the AM EF score: any additional virgin powder used beyond the mass of the final parts, the unusable powder waste, and the recyclable used powder.

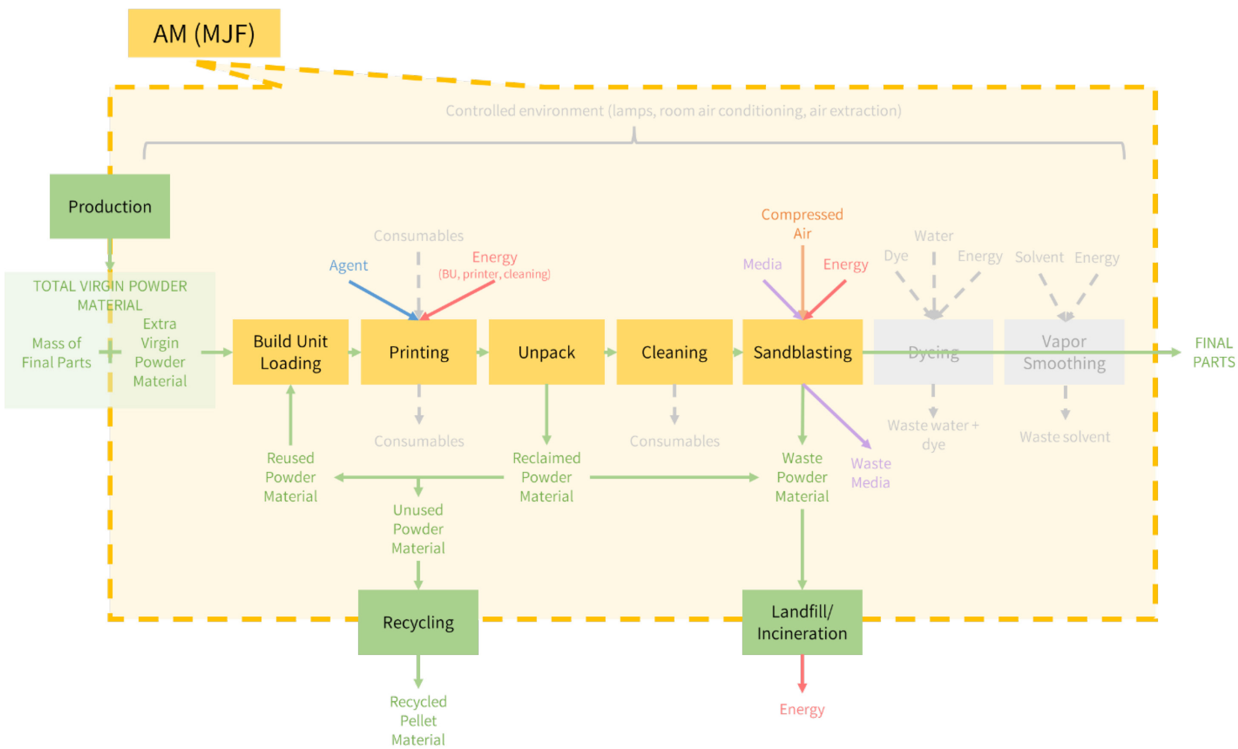

Figure 21. LCA inventory of AM process

For injection molding, however, the step-by-step level of detail was unavailable; therefore, a single EF value from the EF database was used for each geography. The mold impact was obtained by accounting for the mold material production (assumed to be steel) and the mold machine process. The transportation EF score followed the same equation as the transportation cost but replaced the cost per km per ton with the EF score per km per ton. Finally, the end-of-life impact was also a simple multiplication of the EF single score for each disposal process based on the location by the production volume and part weight.

The same limitation of inconsistent location consideration applies here since, across materials, manufacturing, transportation, and end-of-life, only the impact of injection molding, electricity, and transportation and end-of-life was location-dependent.

Equation 2. Set of environmental footprint score calculations leading to the final EF score per part.

EF SCORE PER PART

$$\boldsymbol{EF\ SCORE\ PER\ PART} = [EF\ score_{material} + EF\ score_{manufacturing} + EF\ score_{mold} + EF\ score_{distribution} + EF\ score_{end-of-life}] \div production\ volume$$

EF SCORE OF MATERIAL

Injection Molding:

$$\boldsymbol{EF\ SCORE_{MATERIAL}} = [production\ volume\ (parts)\ x\ part\ weight\ (kg)\ x\ EF\ score_{material\ pellet\ production}]$$

Additive Manufacturing (HP MJF):

$$\boldsymbol{EF\ SCORE_{MATERIAL}} = [production\ volume\ (parts)\ x\ part\ weight\ (kg)\ x\ EF\ score_{material\ powder\ production}]$$

EF SCORE OF MANUFACTURING (& MOLD)

Injection Molding:

$$\boldsymbol{EF\ SCORE_{MANUFACTURING}} = [production\ volume\ (parts)\ x\ part\ weight\ (kg)\ x\ EF\ score_{injection\ molding}] \div Y$$ --- *EF is location dependent*

$$\boldsymbol{Y} = process\ yield\ (\%) = percent\ successful\ parts\ over\ an\ injection\ run$$

Mold (for Injection Molding Only):

$$\boldsymbol{EF\ SCORE_{MOLD}} = mass\ used\ for\ mold\ (kg) x\ [EF\ score_{mold\ material\ production} + EF\ score_{mold\ manufacturing}]$$

Additive Manufacturing (HP MJF):

$$\boldsymbol{EF\ SCORE_{MANUFACTURING}} = production\ volume\ (parts)\ x\ part\ weight\ (kg)\ x\ [\ EF\ score_{AM\ (MJF)}]$$

$$\boldsymbol{EF\ SCORE_{AM\ (MJF)}} = [EF\ score_{material} + EF\ score_{agent} + EF\ score_{sandblasting\ media} + EF\ score_{electricity} + EF\ score_{compressed\ air}]$$

$$\boldsymbol{M} = mass\ of\ printed\ parts\ in\ a\ job\ \left(\frac{kg}{job}\right) = mass\ of\ powder\ in\ BU\ \left(\frac{kg}{job}\right)\ x\ packing\ density\ (\%)$$

$$\boldsymbol{mass\ of\ powder\ in\ BU} = build\ volume\ (cm3)\ x\ material\ powder\ density\ (kg/cm3)$$

$$\boldsymbol{Y} = process\ yield\ (\%) = percent\ successful\ parts\ in\ a\ job$$

$$\boldsymbol{EF\ SCORE_{MATERIAL}} = \left(\frac{1}{M}\right) x \left[\begin{array}{c} \left(mass\ of\ virgin\ powder\ in\ BU\ - M\left(\frac{kg}{job}\right)\right) x\ EF\ score_{material\ production} \\ + mass\ of\ waste\ powder\ \left(\frac{kg}{job}\right)\ x\ EF\ score_{plastic\ incineration-landfill} \\ + mass\ of\ unused\ reclaimed\ powder\ \left(\frac{kg}{job}\right)\ x\ EF\ score_{recycling} \end{array}\right] \div Y$$

$$\boldsymbol{mass\ of\ virgin\ powder\ in\ BU} = mass\ of\ powder\ in\ BU\ \left(\frac{kg}{job}\right)\ x\ material\ loss\ per\ job\ (\%)$$

$$\boldsymbol{mass\ of\ waste\ powder} = M\left(\frac{kg}{job}\right) x\ percent\ waste\ material\ (\%)$$

$$\boldsymbol{mass\ of\ unused\ reclaimed\ powder} = mass\ of\ virgin\ powder\ - M\ - mass\ waste\ powder\ \left(\frac{kg}{job}\right)$$

$$\boldsymbol{EF\ SCORE_{AGENT}} = \left(\frac{1}{M}\right) x\ \left[mass\ of\ agent\ consumed\ in\ a\ job\ \left(\frac{kg}{job}\right)\ x\ EF\ score_{agent\ production}\right] \div Y$$

$$\boldsymbol{EF\ SCORE_{SANDBLASTING\ MEDIA}} = \left(\frac{1}{M}\right) x \left[\begin{array}{c} mass\ of\ media\ consumed\ in\ a\ job\ \left(\frac{kg}{job}\right)\ x\ EF\ score_{agent\ production} \\ + mass\ waste\ media\ \left(\frac{kg}{job}\right)\ x\ EF\ score_{glass\ incineration\ -landfill} \end{array}\right]$$

$$\boldsymbol{EF\ SCORE_{ELECTRICITY}} = \left(\frac{1}{M}\right) x \left[printer + sandblasting\ electricity\ consumption\ \left(\frac{kWh}{job}\right)\ x\ EF\ score_{electricity\ mix}\right] \div Y$$ --- *EF is location dependent*

$$\boldsymbol{EF\ SCORE_{COMPRESSED\ AIR}} = \left(\frac{1}{M}\right) x\ \left[compressed\ air\ used\ \left(\frac{kg}{job}\right)\ x\ EF\ score_{compressed\ air}\right]$$

EF OF DISTRIBUTION

$$\boldsymbol{EF\ SCORE_{TRANSPORT}} = production\ volume\ (parts)\ x\ part\ weight\ (tons)\ x \left[\begin{array}{c} distance\ international\ maritime\ (km)\ x\ EF\ score_{international\ maritime} \\ + distance\ international\ ground\ (km)\ x\ EF\ score_{international\ ground} \\ + distance\ regional\ ground\ (km)\ x\ EF\ score_{regional\ ground} \end{array}\right]$$ --- *EF is location dependent*

EF OF END-OF-LIFE

$$\boldsymbol{EF\ SCORE_{END-OF-LIFE}} = production\ volume\ (parts)\ x\ part\ weight\ (kg)\ x\ [\ EF\ score_{landfill\ or\ incineration\ or\ recycling}]$$ --- *EF is location dependent*

4.2.4. Other Model Assumptions

Some other assumptions beyond the ones mentioned in the previous two sections were made to simplify the complexity of this model. The additive manufacturing environmental impact assessment assumed the impact of material powder, agent, and sandblasting media transportation as negligible since it represents less than 0.01% of the overall EF single score of the AM process. Additionally, for these EF calculations, the rule of thumb of 60% incineration and 40% landfill was applied to each material or consumable waste accounted for. Assumptions were also made to reduce the complexity of injection molding. The number of cavities was set to 1 for all parts analyzed, and the same part thickness was used to determine the cycle time coefficients. Finally, the assembly cost was ignored due to the assumption that all parts could be manufactured in one piece. The assumptions described in this system model overview section can represent model limitations and lead to future modifications and improvements for this analysis.

4.3. Tradespace Analysis

4.3.1. Full Tradespace

*(**Figure 15** process step: Step 7 "Tradespace")*

With the design alternatives, system model inputs, and computations now defined, the tradespace analysis can start. In parallel to generating all possible combinations of options, a recap of the performance results for the set of reference concepts is shown in **Table 11**.

Table 11. *Reference concepts for tradespace analysis with performance results.*

REFERENCE CONCEPTS:

Design ID	Concept Name	Application	Production Volume	Part Size	Material	Mfg Process	Transportation	End-of-Life	EF per Part	Cost per Part
113	Prototype from Add Lab	Prototype/After-Sales Repair	20	50	TPU	AM (MJF)	RER (FR) - RER (FR)	Recycling	158	€ 38.36
107	Prototype IM Equivalent	Prototype/After-Sales Repair	20	50	TPU	Injection Molding	RoW (CN) - RER (FR)	Recycling	4503	€ 1.03
85	After-Sale Repair Part from Add Lab	Prototype/After-Sales Repair	20	50	PA12	AM (MJF)	RER (FR) - RER (FR)	Landfill	215	€ 40.64
79	After-Sale Repair Part IM Equivalent	Prototype/After-Sales Repair	20	50	PA12	Injection Molding	RoW (CN) - RER (FR)	Landfill	4499	€ 0.94
1525	Production Part from Add Lab	Production Part	10000	5	PA12	AM (MJF)	RER (FR) - RER (FR)	Landfill	21	€ 1.52
1519	Production Part IM Equivalent	Production Part	10000	5	PA12	Injection Molding	RoW (CN) - RER (FR)	Landfill	15	€ 0.22

Highlighting the six concepts to the full set of possibilities, a tradespace graph is obtained, as illustrated in **Figure 22**. The axes are placed on the logarithmic scale to better view the range of results generated. Given the assumptions made in the model setup, the values shown on the tradespace should be used as relative measures rather than absolute ones.

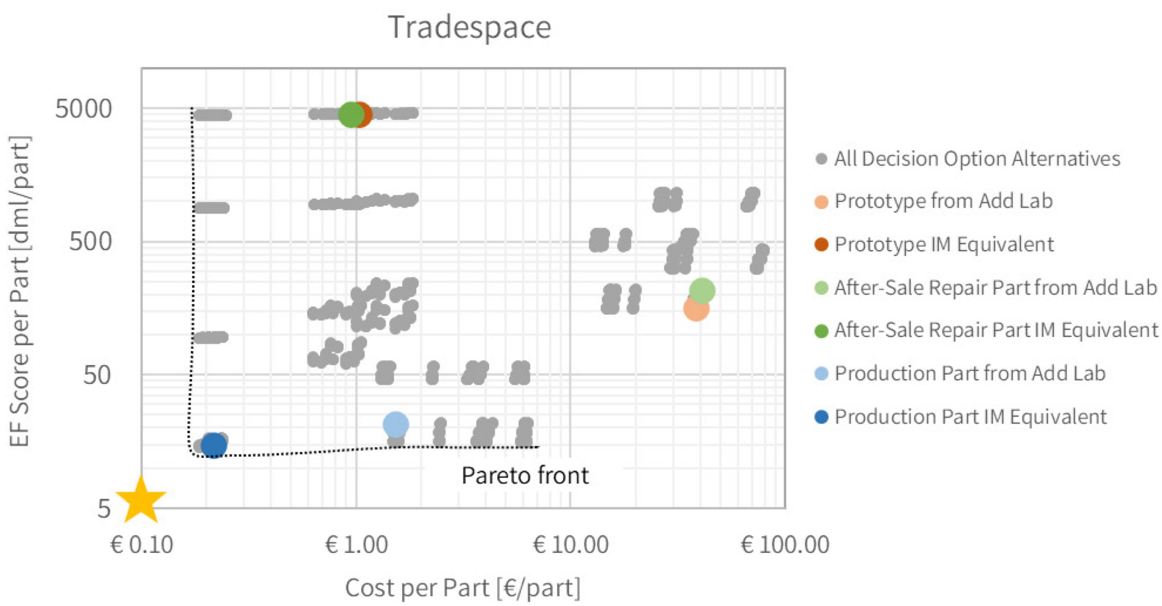

Figure 22. *Full tradespace analysis with reference concepts and the utopia point (start).*

From this initial plot, the average prototype and after-sales parts printed in the Add Lab appear to have a lower EF value compared to their injection molded counterparts. However, for the production part, the injection-molded product has a slightly lower EF score than the AM one. From a cost perspective, injection-molded parts are cheaper than AM parts across applications. For both manufacturing methods, the production parts are cheaper while the prototype and after-sales parts yield a more moderate unit cost. Beyond these observations, it is difficult to discern if the material choice, the manufacturing location, or the end-of-life strategy affects the performance. The general shape of the data points towards the utopia points located at (0,0), meaning that many options lie near the pareto front where the tradeoff between environmental footprint and cost is in direct competition, making it difficult to balance both metrics well.

4.3.2. Tradespace Analysis by Decision

*(**Figure 15** process step: Step 8 "Analysis")*

To extract more valuable insights from this analysis, the tradespace graph was broken down by decision options via the use of colors to assess if trends emerged, as shown in **Figure 23**.

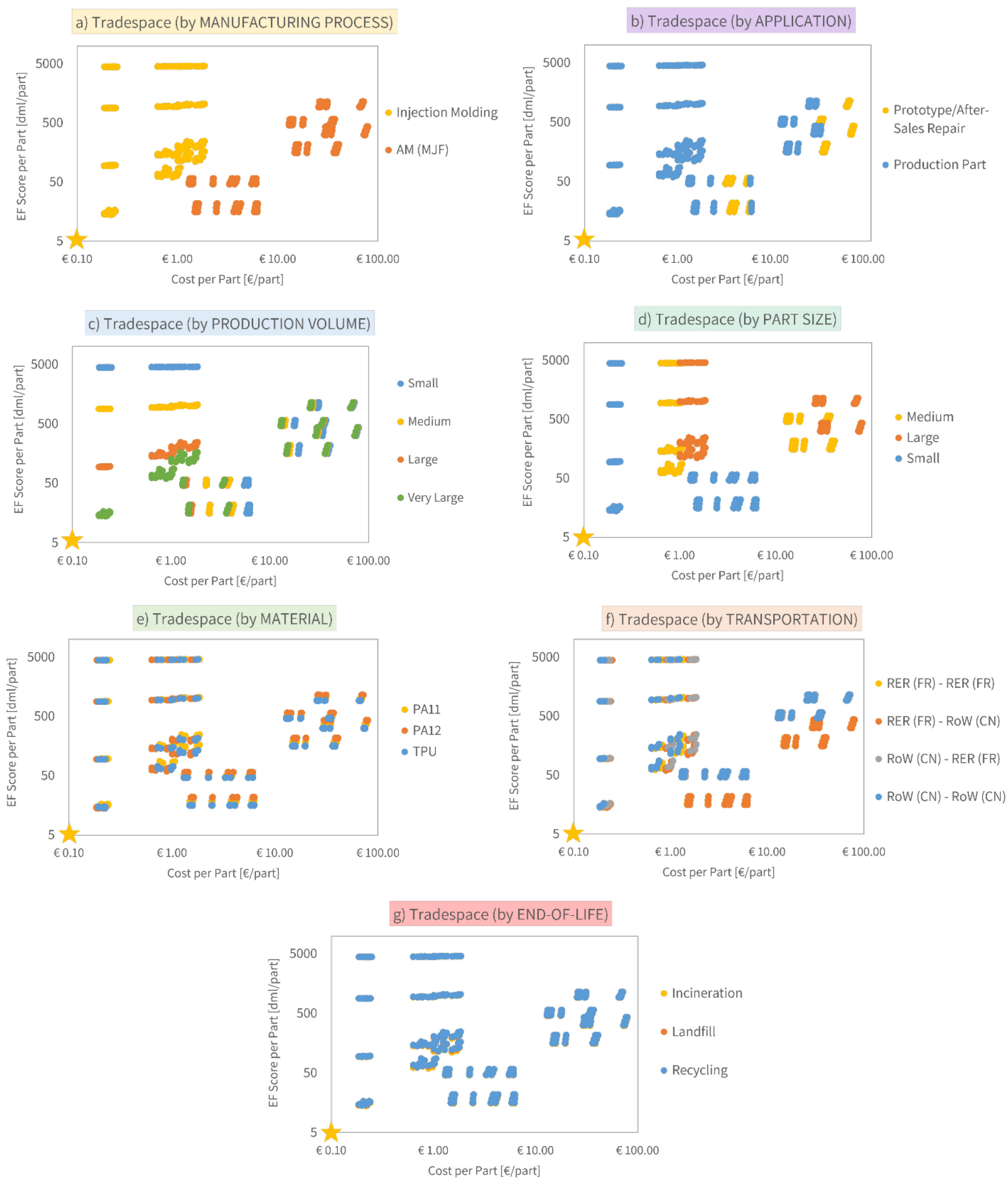

Figure 23. Tradespace graphs split by decision options.

From these charts, trends emerge for five of the seven decisions. The clearest one is the manufacturing process (graph a). AM shows better environmental performance but a greater variance in cost while IM yields lower unit cost but exhibits a greater variance in environmental footprint. Second, for AM parts, the production applications (graph b) seem to yield cheaper results compared to after-sales/prototype parts, but no clear difference is seen on the EF side.

The injection-molded applications perfectly overlap and show no difference between the two options. Third, as the production volume (graph c) decreases for injection-molded parts, the EF score per part seems to significantly increase. This trend is not visible for AM parts. Fourth, smaller part sizes (graph d) tend to generate cheaper unit costs for both manufacturing processes compared to medium and large part sizes. Also, smaller sizes lower EF scores for AM but do not seem to impact the footprint for IM as much unless it is a very large production volume. Fifth, the manufacturing location (graph f) appears to impact the environmental footprint of AM parts (manufacturing in Europe is more environmentally friendly) but not of injection molding parts. For injection molding, the distance between the manufacturing and use locations seems to impact the unit cost (manufacturing locally is more cost-effective).

This preliminary assessment is further analyzed via two more different techniques. Each approach is described below, along with a summary of key learnings.

4.3.3. Mean Comparison using Student's T-Test

To validate some of these qualitative observations and better understand the significance of the differences observed on the tradespaces, a mean comparison between each decision option is performed by running an "Each Pair, Student's t-test" using the statistics software JMP 16. In addition to analyzing the entire dataset, when found significant, the mean comparison results are also split by manufacturing process. For the t-test, if the difference in mean between the data clouds for each option has a p-value lower than 0.05 (see if circles on the right side of the charts overlap or not), it means that the difference is significant. The t-test analysis shows that:

- Starting with the manufacturing process, the t-test confirms that injection molding has a larger environmental footprint but a lower unit cost than AM. On average, the injection molding unit cost is 97% cheaper than the unit cost of AM parts. On the EF score side, AM's score is, on average, 75% lower than injection molding's EF score. The next analysis technique will dive deeper into the tradeoff between the two processes.

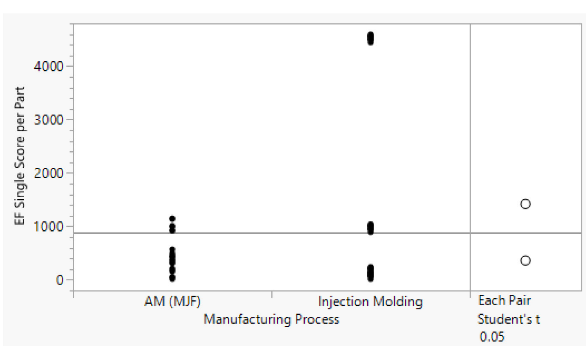

Figure 24. T-test EF score versus manufacturing process

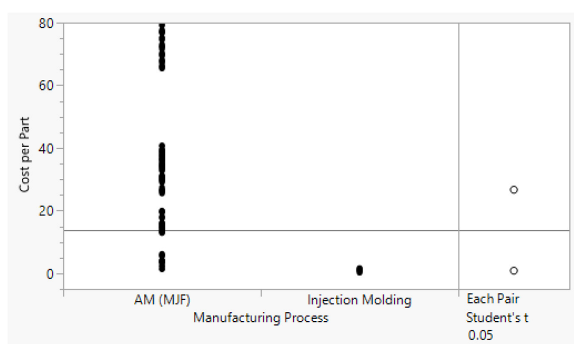

Figure 25. T-test cost versus manufacturing process

- Overall, all applications perform the same in terms of environmental footprint. This is because the same product characteristics are evaluated for each application, and EF scores are driven by weight. Regarding the unit cost, production parts seem significantly cheaper than prototypes/after-sales repair parts. However, breaking down **Figure 27** by manufacturing process, this difference is only visible with additive manufacturing, where production parts are, on average, 58% cheaper than prototype/after-sale repair parts. This behavior is driven by the uniform build configuration, enabling higher build utilization and throughput, leading to better economies of scale. This aligns with the observations from Baumers et al. [74]. The injection molding costs are the same regardless of the application, which highlights a limitation of the model since it is known that a prototype part would typically be more expensive than a production part [70]. In future work, the production quantity of prototypes or after-repair sales should be limited to smaller amounts than production parts and a different accounting of tooling costs should be applied.

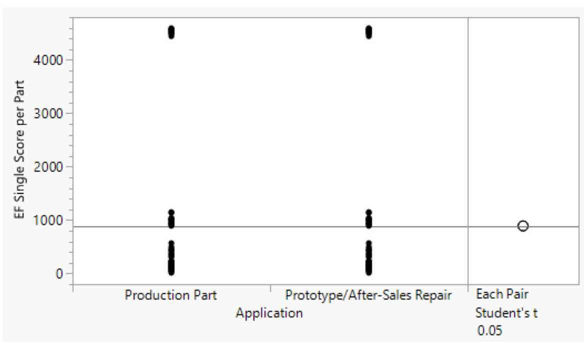

Figure 26. T-test EF score vs application

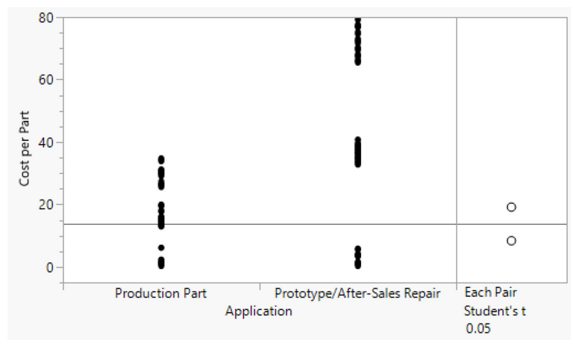

Figure 27. T-test cost versus application

Breakdown for cost by manufacturing process:

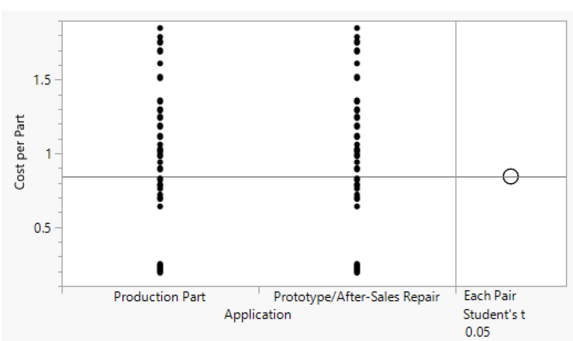

Figure 28. T-test cost vs application (IM only)

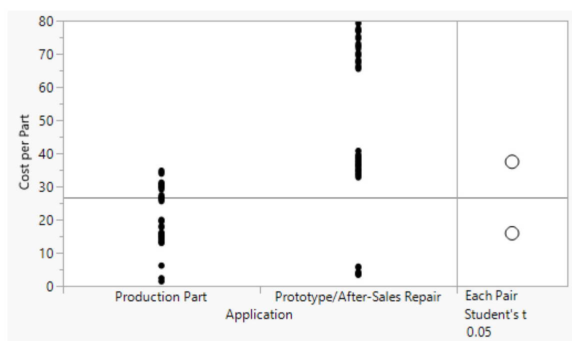

Figure 29. T-test cost vs application (AM only)

- On the environmental side, small production runs of parts seem significantly more environmentally impactful than the three other demand volumes. When analyzing this decision by manufacturing process, this trend is only seen with injection molding (**Figure 32**), where the EF scores scale with lower production volume. In fact, with a smaller production volume, the impact of the injection mold becomes more significant, raising the environmental impact per unit. On average, the EF score per unit for a 10,000-

part production volume is 98% lower than the one for a 20-part volume. The EF score of AM is not impacted by production volume since no additional tooling is needed with this process. From a cost perspective, there are no significant differences between the production volumes when looking at the entire dataset in **Figure 31**. Breaking it down by manufacturing process does not yield significant differences either. For injection molding, this can be explained by the cost equation logic, which only accounts for the percent utilization of every cost center (i.e., mold, machine, etc.). This method does not represent economies of scale well, which represents a potential limitation to this analysis. For additive manufacturing, the observation made on the effect of the type of application in **Figure 29** led to the breakdown of the data by application. There, it is observed that production parts (printed in uniform builds rather than mixed builds) experience a decrease in unit cost as the production volume increases (**Figure 34**). The unit cost for a production part produced in a very large volume is, on average, 25% lower than when it is produced in a small volume.

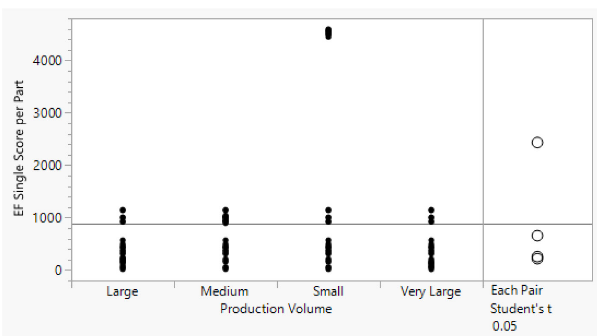

Figure 30. *T-test EF score vs production volume*

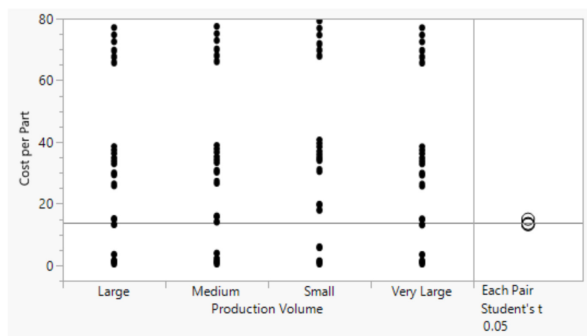

Figure 31. *T-test cost vs production volume*

Breakdown for EF score by manufacturing process:

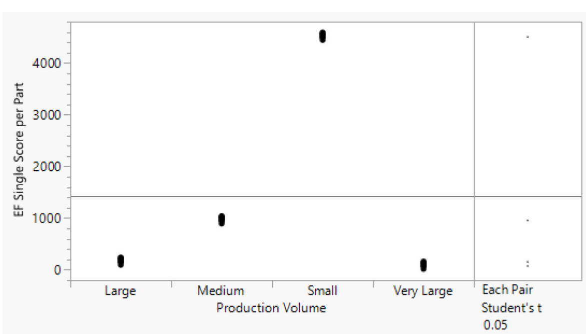

Figure 32. *T-test EF score vs production volume (IM only)*

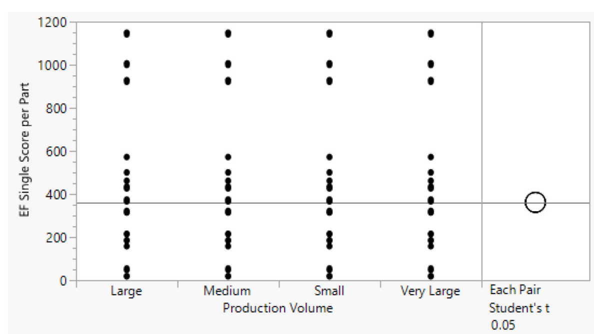

Figure 33. *T-test EF score vs production volume (AM only)*

Breakdown for cost, for AM only, by application:

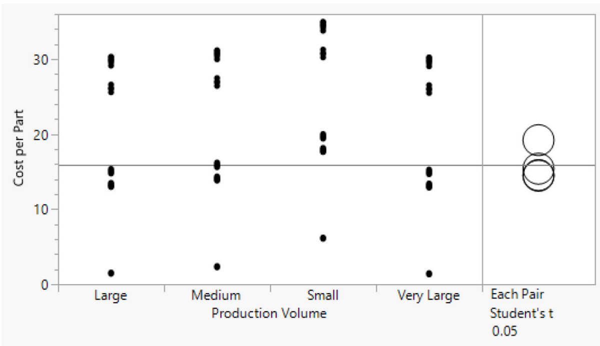

Figure 34. T-test cost vs production volume (AM + production part only)

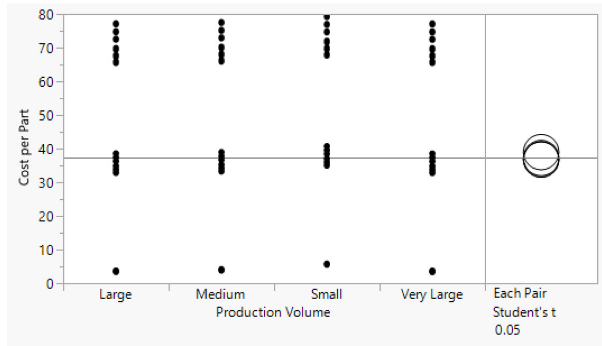

Figure 35. T-test cost vs production volume (AM + prototype/after-sale repair part only)

- Smaller part sizes seem to significantly reduce the environmental impact. This is logical since the EF score directly scales with weight since the functional unit used in the LCA inventory is 1 kg of part manufactured. Breaking the data by manufacturing process shows that AM experiences this trend significantly (**Figure 39**), while injection does not. This might be due to the injection mold EF impact drowning the effect of the material. For AM, printing smaller parts reduces the EF score by 95%, on average, compared to large parts. In a similar trend, the smaller the part size, the cheaper the unit cost. On average, a smaller part size reduces unit cost by 93% compared to a large part size. This makes sense for both manufacturing processes as smaller parts mean more parts can fit into one AM build (higher capacity utilization and throughput), and the cycle time in injection molding is shorter, which equals less equipment utilization.

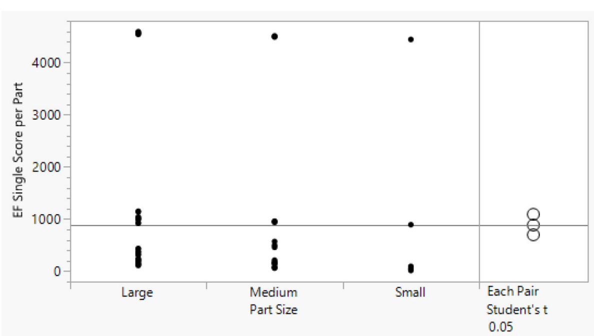

Figure 36. T-test EF score versus part size

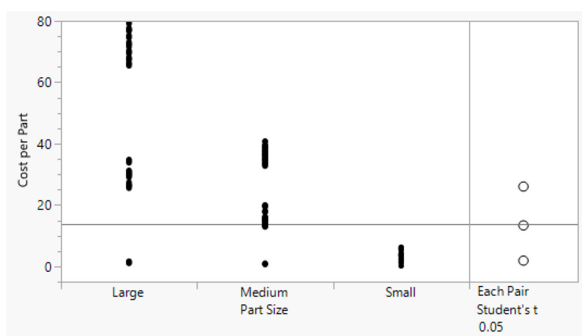

Figure 37. T-test cost versus part size

Breakdown of EF score by manufacturing process:

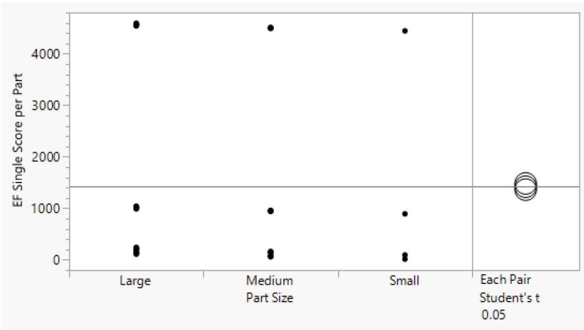

Figure 38. T-test EF score versus part size (IM only)

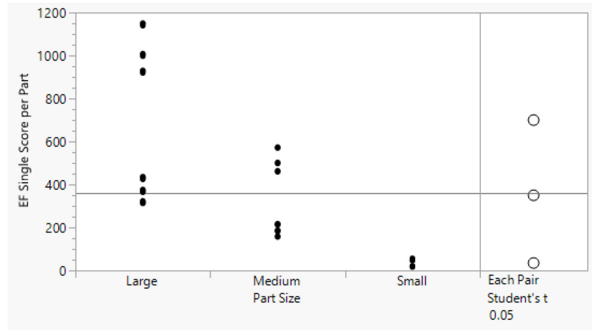

Figure 39. T-test EF score versus part size (AM only)

- When considering all the data, the material choice does not seem to matter for the EF score or the unit cost. However, breaking it down by manufacturing process shows that TPU yields a significantly lower EF score than PA12 for AM parts (on average, 21% lower score), and PA12 yields a significantly lower unit cost than PA11 for injection molded parts (on average, 14% lower cost). There was no difference in cost across materials for AM parts and no differences in EF across materials for injection molded parts. It is interesting to observe that material choice matters for environmental footprint in AM but matters for cost in injection molding. For the AM observations, it will be interesting to re-evaluate once the updated EF scores of AM materials are confirmed. In fact, this behavior might be an artifact of the assumptions made on the EF scores since the values were missing from suppliers.

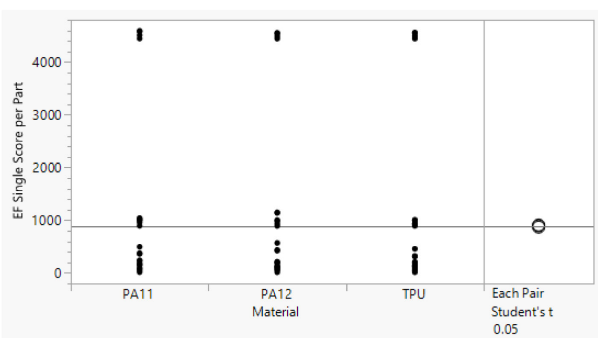

Figure 40. T-test EF score versus material

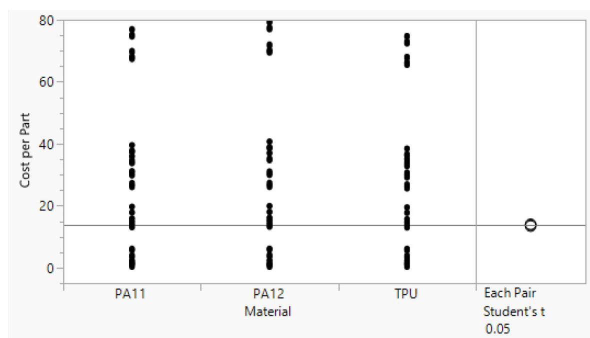

Figure 41. T-test cost versus material

Breakdown of EF score by manufacturing process:

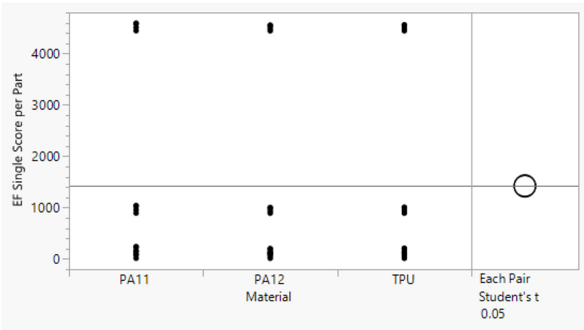

Figure 42. T-test EF score versus material (IM only)

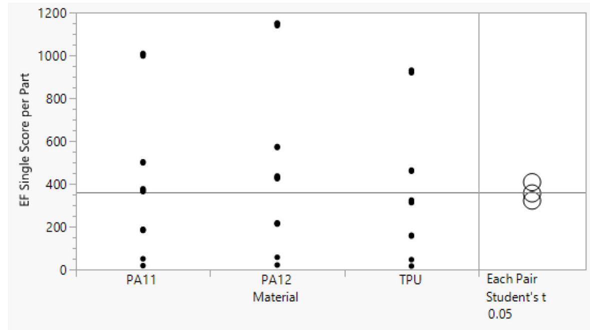

Figure 43. T-test EF score versus material (AM only)

Breakdown of cost by manufacturing process:

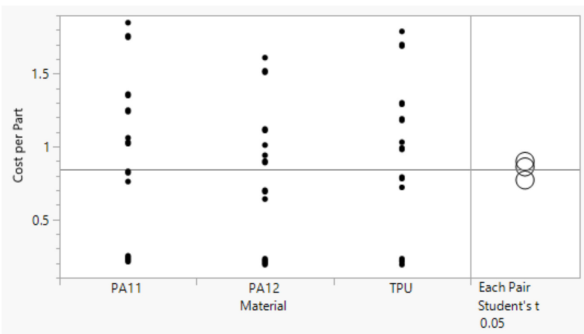

Figure 44. T-test cost versus material (IM only)

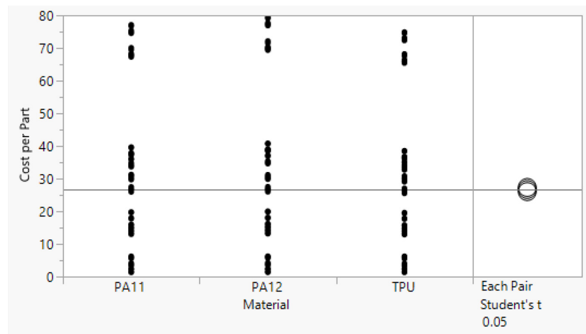

Figure 45. T-test cost versus material (AM only)

- For transportation, a similar story is observed: overall, no significant difference is noticeable, but when breaking down the data by manufacturing process, trends emerge, showing an interaction between the two decisions. For AM, the manufacturing location significantly matters, as parts produced in Europe (RER) exhibit, on average, 64% lower EF score than parts manufacturing in China (RoW) (see **Figure 49**). This must be caused by the different energy footprints in the two locations since it is the only factor dependent on location in the AM footprint calculations. The transportation scheme of 3D-printed parts does not impact the unit cost, but it does impact the cost of injection molded parts (**Figure 50**). Manufacturing parts near the use location (local production) lowers the unit cost by 27% compared to international manufacturing. This observation shows that given the generally low unit cost of injection molded parts, transportation starts to matter, while for AM, the contribution of transportation cost is much lower in proportion. This observation could also be driven by the assumptions made for the ground transportation costs.

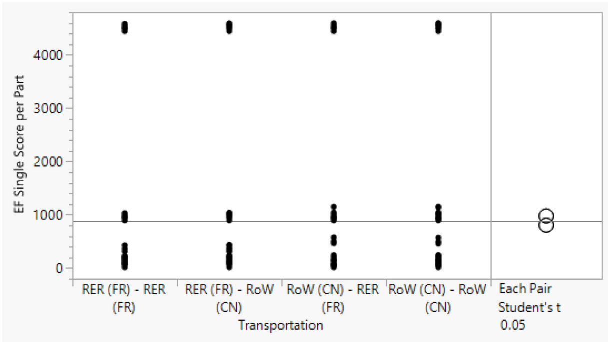

Figure 46. T-test EF score versus transportation

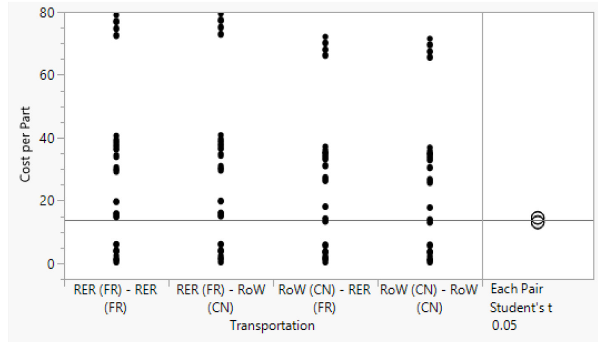

Figure 47. T-test cost versus transportation

Breakdown of EF score by manufacturing process:

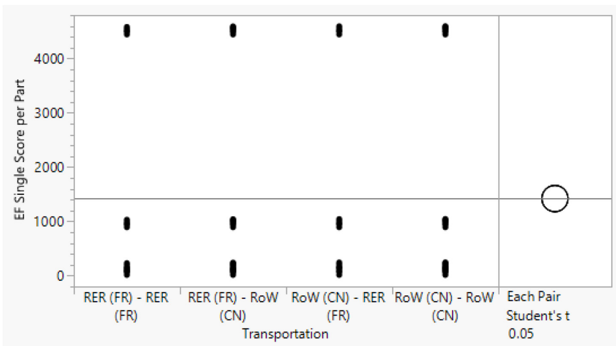

Figure 48. T-test EF score versus transportation (IM only)

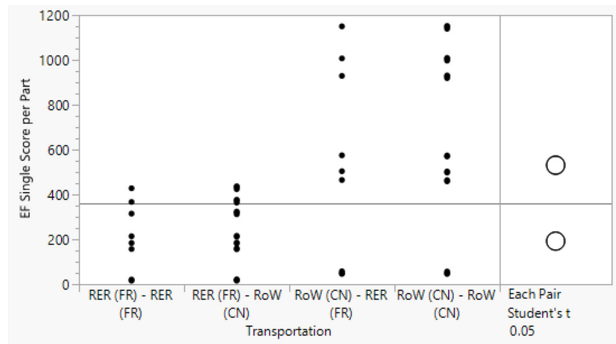

Figure 49. T-test EF score versus transportation (AM only)

Breakdown of cost by manufacturing process:

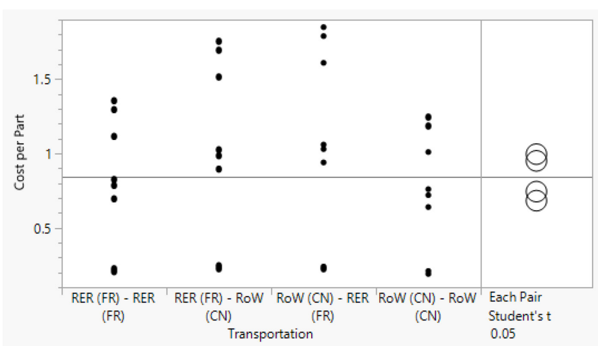

Figure 50. T-test cost versus transportation (IM only)

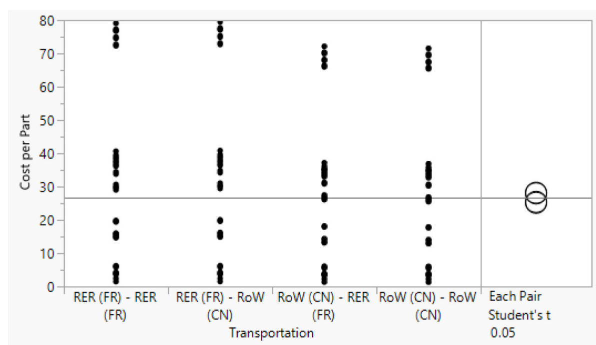

Figure 51. T-test cost versus transportation (AM only)

- There is no significant difference in cost or EF between the three end-of-life strategies. For the cost, the explanation is clear since it is not accounted for in the unit cost calculations. However, for EF score, it is more surprising given that each strategy has a different environmental footprint. This observation means that the relative contribution of end-of-life paths does not matter compared to the environmental impact of the material, manufacturing, and transportation.

Now that the significance of the differences between decision options is clarified and some interactions with the manufacturing process have been uncovered, let's dive deeper into the tradeoffs between additive manufacturing and injection molding.

4.3.4. AM vs IM Tradeoff Tradespace Analysis

To visualize the tradeoffs between the two manufacturing processes, a new tradespace analysis was performed. Instead of plotting the EF single score per part versus the cost per part, now, the EF and cost deltas between IM and AM are calculated for each part type and lifecycle decision alternative and plotted below in **Figure 52**. To help interpret these graphs, since AM values were subtracted from IM values, if the value is positive, AM is performing better, and if the value is negative, IM is performing better.

As a first major insight from these tradespace graphs, the cost of each alternative is negative while the EF score ranges from negative to positive values. This means that, for none of the scenarios simulated in this analysis, additive manufacturing is more cost-effective than injection molding. AM can only compete on environmental footprint. This observation has significant implications for the value proposition of a team like Add Lab. However, on the one hand, it was highlighted that the reliability of the model inputs should be verified and updated, which could lead to different results. On the other hand, design benefits of 3D, such as lightweighting, were not considered in this analysis and could alter the tradeoff space between the two processes. Despite this general observation, recommendations can still be drawn from these graphs to define which part and lifecycle parameters can improve the value of AM and which lead to IM being more adequate.

First, as seen in the t-test, production parts (graph a) printed in a uniform build configuration can improve the unit cost of AM compared to prototype and repair parts placed in a mixed build configuration. While the choice of an application does not change the environmental footprint, selecting production parts appears better to make AM more financially competitive than prototype/after-sales repair parts. Second, the production volume (graph b) does not affect the cost tradeoff between AM and IM. However, by manufacturing small volumes, AM gains an advantage in the environmental footprint performance. When the volume becomes larger (100 to 10,000 parts), the environmental footprint of IM parts becomes more attractive compared to AM. Third, AM clearly shows more financial competitiveness when producing small part sizes (graph c) as it significantly reduces unit cost compared to medium and large sizes. This makes IM very attractive when considering large, heavy parts, which aligns with the findings from Kazmer et al. [124] and Mecheter et al. [76]. On the environmental footprint side, small part sizes also seem to provide an advantage to AM, as most of the data lies on the positive side of the EF axis. Fourth, the material choice (graph d) does not appear to have a big influence on the adequacy of one manufacturing process over another. However, when looking at interaction across decisions, for prototype/after-sale repair parts with large sizes (left area of the graphs), PA12 is more attractive from a cost and EF score perspective than other materials for injection molding. Fifth, in general, manufacturing in Europe (graph e) has an environmental benefit for AM compared to IM, especially for larger prototype parts. However, manufacturing in China may offer the least delta between AM and IM in terms of cost. For clarity, note that for the transportation tradespace, yellow and orange overlap, and blue and grey overlap. Finally, as seen thus far, the end-of-life strategy (graph f) does not provide an advantage for either manufacturing process, since all the points perfectly overlap.

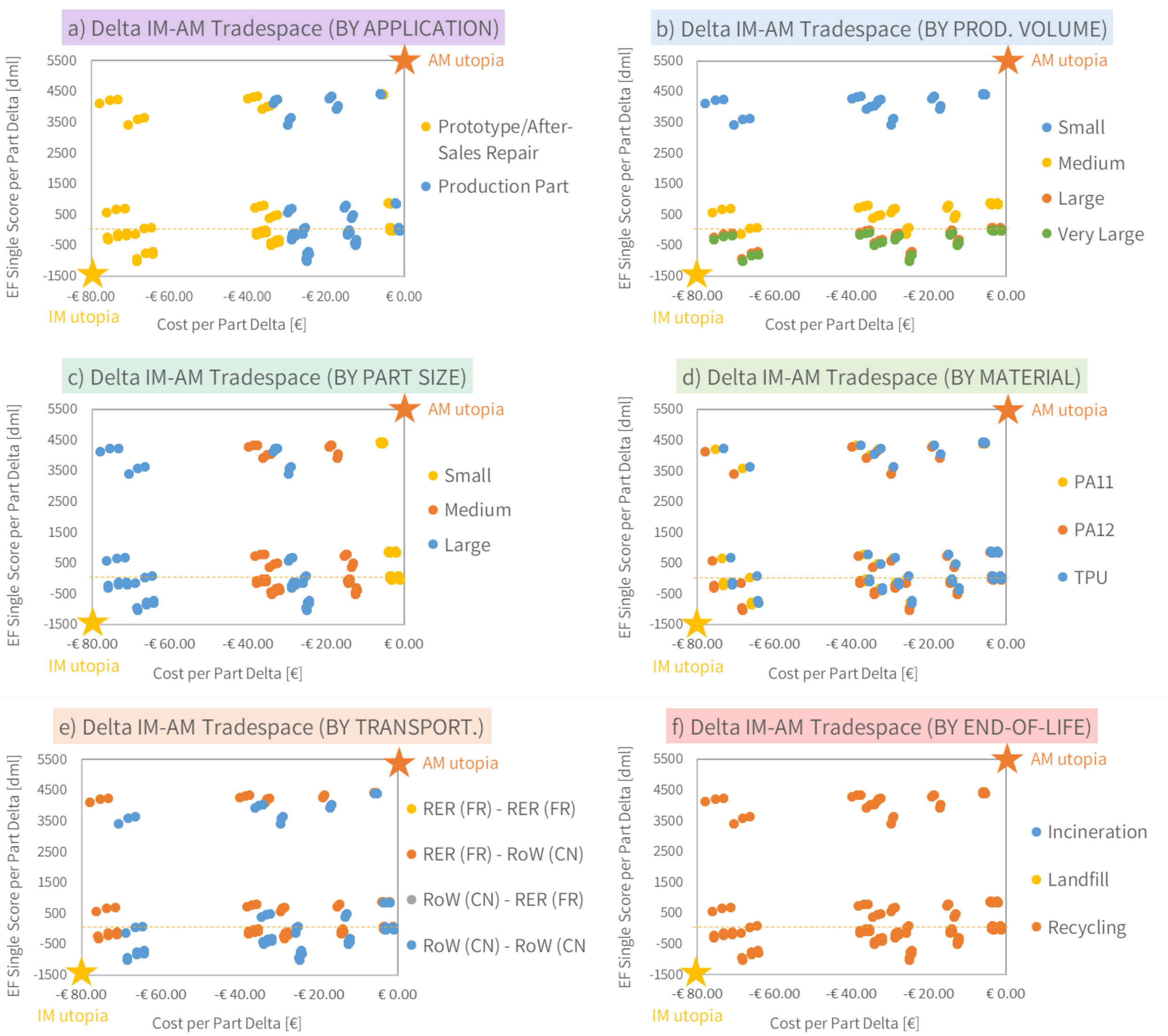

Figure 52. Tradespace graphs split by decision and showing EF and cost tradeoff between IM and AM.

To summarize these tradeoff observations, let us characterize the points closest to the AM and the IM utopia points, as shown in **Figure 53**. For AM, the consistently more advantageous product characteristics and lifecycle path options include small production volume and small part size. The application, material, and transportation scheme represent a tradeoff between cost and EF score, and the end-of-life strategy does not make a difference. For IM, the consistently competitive decision options are prototype/after-sales repair parts, very large or large production volume, large part size, and PA12. The transportation scheme shows tradeoffs between EF score and cost; the end-of-life strategy does not matter either.

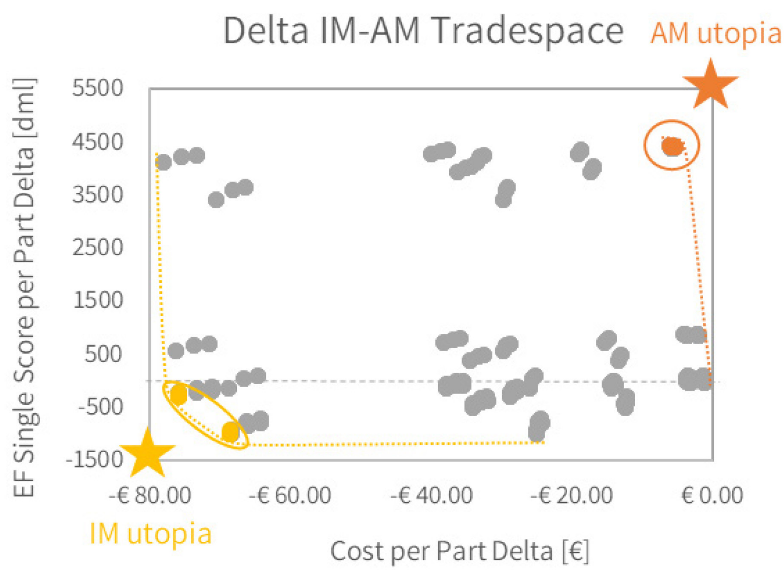

Figure 53. *IM-AM Delta Tradespace*

4.4. Analysis Recommendations & Limitations

4.4.1. <u>Turning Tradespace Analysis Insights into Strategic Decisions</u>

The analysis reveals several key insights into the environmental and cost tradeoffs between additive manufacturing and injection molding. It also shows that the product characteristics and lifecycle decisions investigated demonstrate three types of influence on unit cost and EF score: (1) some decision options improve both metrics, (2) some options constitute a tradeoff between unit cost and EF score, and (3) some decision options have no impact on EF or cost.

The major finding of the study is the contrast between the inability for AM to be cost competitive with IM across all decision options evaluated and its general tendency to be more environmentally friendly. In fact, IM is, on average, 97% cheaper than AM, but AM yields, on average, a 75% lower EF score than IM. This observation is encouraging as companies are starting to value sustainability performance as much as economic value, but it also highlights the need for 3D printer and material manufacturers to continue finding opportunities for cost reduction.

The second set of learnings consists in identifying the options and decisions augmenting the value of each manufacturing process and showing in which scenario AM needs to step up. Small part sizes combined with small production volumes are options that maximize the environmental and economic performance of AM. In contrast, the options for application, material, transportation, and their combinations show a tradeoff between EF and cost. To optimize the financial and environmental value of IM, prototype/after-sales repair parts, large or very large production volumes, large part sizes, and PA12 are adequate options to select. Various transportation schemes show a tradeoff between EF score and cost. Across both processes, the end-of-life strategies do not show a significant difference in performance due to their low contribution to EF score and unit cost.

Third, based on the options maximizing the performance of AM and other general observations from the analysis, decision recommendations for Add Lab and its suppliers can be extracted. First, Add Lab should prioritize small production runs with part characteristics that maximize the build capacity utilization and throughput of the MJF printers, such as small part sizes and production applications. Compared to injection molding, small production runs enable AM to deliver unique value on the environmental sustainability front (on average, 92% lower EF score) by avoiding the large impact of an injection mold. Beyond the fact that smaller parts lead to smaller EF scores since this metric is weight-driven, the uniform builds filled with small parts is a recommendation in line with the findings from Baumers et al. on drivers for economies of scale for AM [74]. However, knowing that mixing parts in a single job is one of the key advantages of AM [72], especially for low or irregular demand volumes or multi-component parts [54], there might be a balance to be struck on a case-by-case basis. While aiming for improved utilization of the build volume in AM, a better understanding of the cost of traditional manufacturing for low-volume orders, the supply chain associated with multi-component assembly, and the cost of time would help paint a more objective picture. The second recommendation is to maintain manufacturing in Europe regardless of the use location, as manufacturing in France lowers EF scores by, on average, 64% compared to producing in China. This trend is driven by the difference in environmental impact of the energy mix between the two geographies. Therefore, the footprint of the electricity source represents a lever for deciding where to locate AM capabilities and also becomes a vital area of improvement to reduce the technology's environmental impact as seen in the study from Tagliaferri et al. [129].

In summary, the analysis underscores the complex tradeoffs between AM and IM, emphasizing the need to carefully consider part characteristics and lifecycle factors. It also highlights areas of improvements for 3D printer manufacturers. The results of the tradespace model provide an initial set of recommendations, although re-evaluation of the input parameters and validation of the final performance values are needed, given the model limitations uncovered during the data analysis.

4.4.2. Model Limitations

This first attempt at assessing the tradeoffs and impact of decisions on a product lifecycle comes with limitations that require investigation for future model development work.

1. In general, given that some EF single score values were missing (material powders, printing agents, regional transportation in China) or not considered (controlled environment or printing consumables), an updated analysis will be needed once this data is available. Alternatively, another impact indicator available across the board, such as climate change, could replace the EF single score metric. The influence of material choice might be better quantified this way since no large effect was observed with the assumptions made here.
2. Another general limitation lies in the location dependence not being consistently applied across all the cost or environmental impact metrics. This may hinder the full performance impact of manufacturing and end-of-life location even though some trends have already emerged in this study. Slightly tied to location dependence, the presence of automation tools and other labor-related enhancements is also an important parameter to consider, as it might alleviate labor costs but impact equipment costs and environmental criteria.
3. Regarding the additive manufacturing process, several parameters were averaged across a set of print job data and assumed constant despite a potential dependence on material or other variables. These include the packing density of the job, which is often lower for jobs printed with TPU versus PA12 and can widely vary based on the part geometry, the amount of electricity consumed during the printing phase, which depends on the printing temperature needed to fuse each material, or the amount of compressed air consumed during sandblasting since it depends on how rough and sticky the surface of a part might be. Adding the material dependency (or other variable dependency) and considering a distribution of values rather than a static, deterministic point could help better capture this behavior in the model. This consideration for uncertainty should be applied to more parameters in this model than just the ones related to AM.
4. Many assumptions made for the injection molding process also represent limitations. First, no minimum production quantity was imposed for this process, which may be wrong depending on the type of application. A production run of 20 parts may not be a feasible option, as injection molding manufacturers would often require a larger volume to be produced, forcing the need for a surplus/spare inventory. The cost of inventory or premium pricing in case of lower production runs was not considered in this analysis. Secondly, assembly costs and EF should also be depicted in the model as they are among the major differences between the two manufacturing processes (i.e., AM should require fewer assembly steps), and their impact would be interesting to quantify. Third, scrap

material was ignored in the material cost equation, which may be misleading since scrap material in injection molding has a monetary value. Finally, the assumptions around the injection mold were heavily simplified, and factors such as the availability of rapid prototyping for short-run injection molds, the selection of a different material to manufacture a mold, or the varying life expectancy of molds would add richness to the analysis.

5. Case Study: Flexible Design Analysis

5.1. Analysis Objective & System Boundaries

*(**Figure 16** process step: Step 1 “Objective”)*

The objective of the flexible design analysis, the second methodology used in this case study, is to answer the remaining research questions:

- #2b: Is it worth incentivizing suppliers through investments such as co-development efforts?
- #3a: Should Add Lab consider expanding its capacity to support the growing demand in-house or continue leveraging service bureaus to handle any additional demand as they do today?
- #4: Should Add Lab upgrade its facility energy source to meet environmental goals? Is the investment worth the environmental gain?

Rather than product- or lifecycle-related decisions, this analysis is focused on defining investment strategies that will improve the environmental performance of Add Lab’s 3D printing services while ensuring continued growth (through adequate capacity to support the growing demand) and profitability (by achieving a positive NPV). The analysis addresses the questions by generating and evaluating a set of flexible AM strategy options revolving around supplier incentive investments, capacity expansion through facility rental, and energy source alternatives after understanding the performance of the current operational setup of Add Lab. The intent is to determine the operational capability levers Add Lab could put in place to support its current and future product portfolio as well as the company’s commitment to reduce its product environmental footprint and global emissions, and encourage its suppliers to take action towards environmental sustainability.

To perform this evaluation, an analytical tool in Excel is developed to model the system (i.e., product portfolio and Add Lab capacity) performance based on environmental footprint, cost, and revenue metrics. Defining the current product portfolio and capacity the business unit supports as the starting point, this analysis is carried out over a 10-year time frame and considers a realistic set of choices and decisions the team will be faced with over that duration. A longer period was not considered, given the rate at which 3D printing technologies are evolving and the high uncertainty around future product demand. Speaking of uncertainties, this model includes sources of uncertainty stemming from the recent initiatives from 3D printing suppliers, the ongoing development of the technology, and the demand projections for current and new products. It will assess the impact of these non-deterministic values using Monte Carlo simulations. Unlike the tradespace analysis, this model is based on a cradle-to-gate life cycle approach, starting with raw material production and ending with the finished goods exiting manufacturing, as shown in **Figure 54**. The manufacturing phase encompasses the dynamic decision of outsourcing production to service bureaus when the Add Lab in-house capacity is exceeded, and the subsequent lifecycle steps are assumed to be equal across the strategies investigated, hence their exclusion from this study.

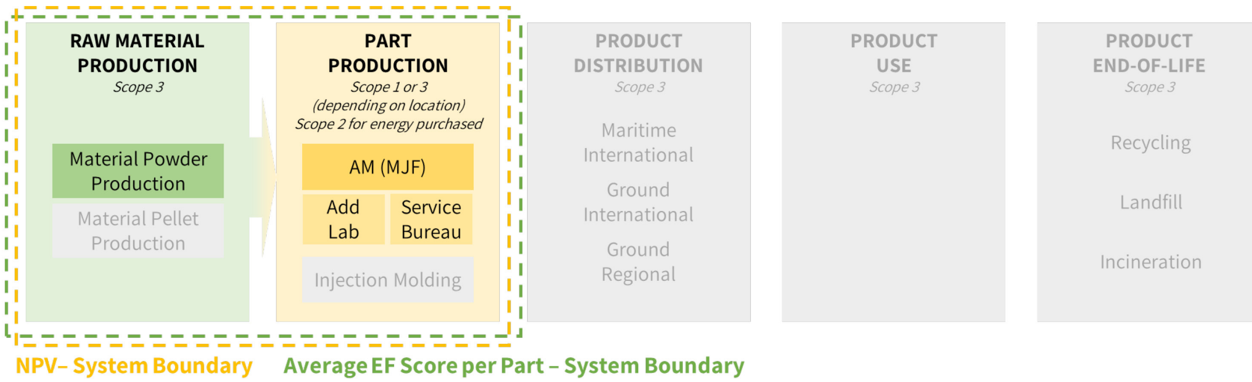

Figure 54. *Flexible design analysis lifecycle level system boundary.*

Flexible Design Analysis Problem Statement:

TO develop real, sustainable, and profitable investment strategy options for the Add Lab team at Decathlon regarding its AM services

BY considering evolving technological advancements and an uncertain market

USING a flexible design analytical model integrating probabilistic distributions, decision rules, and performance simulations

5.2. System Model Overview

5.2.1. Current Add Lab Strategy and Architecture Framework

*(**Figure 16** process step: Step 2 "Metrics")*

To build the system model and investigate the influence of product demand and process improvements on overall financial and environmental performance, four key frameworks centered around the HP MJF 3D printing process were created in Excel, as shown in **Figure 55**. The first one describes the characteristics of the product portfolio, which is defined by the type of applications the Add Lab manufactures (i.e., prototypes, after-sales repair parts, and production parts) and their respective characteristics influencing the demand (i.e., the yearly demand, the average order size, and the average part size for each application). The second module describes the capacity of the Add Lab, which ultimately dictates what portion of the product demand can be manufactured in-house versus outsourced to local service bureaus. Given that Decathlon has relationships with multiple service bureaus in the area, no capacity constraints are associated with orders fulfilled externally. Information about the cost of outsourcing will be provided below. The third framework consists of the cash flow model, which draws from a cost and a revenue model, and scales with the demand. The final and fourth section relates to the environmental footprint calculations stemming from the same LCA method, as explained in **Figure 21**. The performance outputs of this model, NPV and average EF score per part, are slightly different from the tradespace model outputs as the focus is placed on the performance of the entire Add Lab service rather than the performance of a specific part.

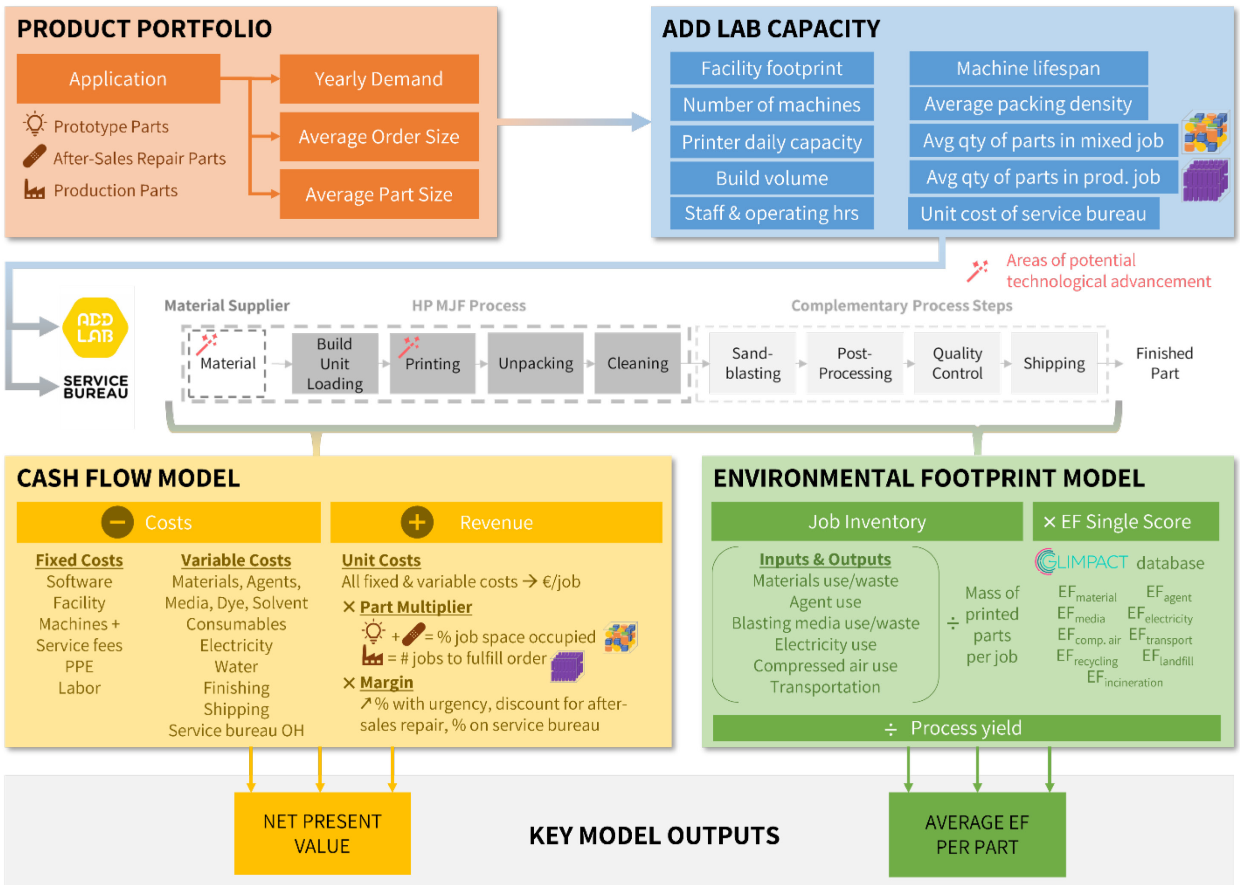

Figure 55. Visual representation of the four key frameworks composing the system model, highlighting the flow between the input variables and the model outputs. The four frameworks include the product portfolio definition and characteristics (orange), the Add Lab capacity (blue), the costing model (yellow), and the environmental footprint model (green).

5.2.2. Input Parameters from Available Information

*(**Figure 16** process step: Step 3 "Inputs")*

The company provided most of the values behind the variables shown in **Figure 55** via past and projected production volume data for each application, current capacity information, the Add Lab costing model, and the environmental footprint measurements and methods developed by Decathlon following the PEF framework.

For the yearly demand volume, Add Lab's projections for the next 10 years were based on the actual number of parts 3D printed in 2023. Similarly, a yearly average of each application's order size and part size was calculated based on 2023 data. These input variables can be found in **Table 12**.

__Table 12.__ Actual and projected yearly demand volume for the Add Lab product portfolio.

Yearly Demand Volume	**Units**	**Year 1**
Prototypes	parts/year	27,000
After-Sales Repair Parts	parts/year	3,000
Production Parts	parts/year	275,000

Average Order Size	**Units**	**Year 1**
Prototypes	parts/order	2
After-Sales Repair Parts	parts/order	1
Production Parts	parts/order	5,000

Average Part Size	**Units**	**Year 1**
Prototypes	g	35
After-Sales Repair Parts	g	50
Production Parts	g	5

The Add Lab capacity parameters were also all provided by Decathlon, as shown in **Table 13**.

__Table 13.__ Actual capacity parameters for the Add Lab product portfolio.

Parameters	**Value**	**Units**
Facility footprint	40	m2
Number of operators	2	operators
Number of engineers	1	engineers
Working hours in a day	8	hrs/day
Working days in a year	250	days/year
Number of printers	2	printers
Build volume	59850	cm3
Packing density	7	%
Daily printer capacity	1.5	jobs/printer/day
Number of jobs per year	750	jobs/year
Average mixed build parts per job	60	parts/job
Average production parts per job	838	parts/job
Number of other machines	…	machines
Machine lifespan	4	years

For the cost parameters, the derivation of the Add Lab costing model was used again. In order to simulate various flexible strategies, this unit costing model was broken up into two separate sections: one for costs and one for revenues. For the cost model, fixed costs (one-time and recurring) and variable costs were separated, as shown in **Table 14**. The specific value of each parameter will not be shared in this document due to data privacy.

Table 14. *List of fixed and variable costs used for the costing model.*

Fixed Costs	Value	Units
Software		€/year
Facility		€/m2/year
Printer		€
Vacuum		€
PPE		€/year
Sandblasting machine		€
Sandblasting CarePack		€/year
Dyeing machine		€
Vapor smoothing machine		€
Vapor smoothing CarePack		€/year
Keyence machine		€
Operator salary		€/hr
Engineer salary		€/hr
Total labor		€/year

Operating Costs	Value	Units
Material		€/kg of material
Agent		€/kg of material
Electricity		€/kWh
Printer consumables		€/job
Sandblasting media		€/job
Water		€/job
Dye		€/job
Vapor smoothing consumable		€/job
Finishing		€/order
Shipping		€/order
Service bureau overhead		€/order

On the other hand, for the revenue model, the accounting method followed by Add Lab was kept intact since this method is used to set pricing and, therefore, dictate revenue. In essence, the revenue model is based on the same set of variables as shown in **Table 14**, but accounts for them differently, reducing them down to a cost per job, which then can be converted into a cost per order based on the type of application produced. This is based on the same cost calculation as used for the tradespace analysis. For production parts, all the jobs to complete the order are uniform since there is a large enough volume to fill entire build units and the entire order is placed at once. Therefore, the total number of jobs to complete the order is used to scale the costs. For prototype and repair parts, one print job is composed of several parts of different geometries, given the smaller and irregular nature of the demand. For this reason, the variable costs are multiplied by the percent space occupied by the order based on what an average "mixed" job looks like. **Figure 19** shows an illustration of both types of jobs.

Other key parameters for the revenue model include the profit margins and price discounts that are applied to each unit cost. Prototypes and production parts are sold with a profit margin, while the repair parts are sold with a profit margin and at a discounted price. It is necessary for Decathlon to apply this discount for repair parts to bring sale prices down. Otherwise, the customers would not choose to repair their broken part and instead, would purchase a brand-new product (which costs more for Decathlon and has more impact on the environment) or decide to throw away the product altogether. The Add Lab believes repairing a product with AM better aligns with its sustainability and circularity goals as it reduces the need for inventory and offers an option to extend the product's life. The Add Lab also uses a margin scale to apply a premium policy when customers place urgent orders. This policy does not apply if a part is produced at a service bureau. For service bureaus, the unit cost is considered to be roughly 30% cheaper than what the Add Lab team offers. The cheaper cost is a result of negotiations between Decathlon and the service bureaus in addition to the application development work (design validation and process validation) Add Lab does upstream. The parameters used in the model are shown in **Table 15**. The equations illustrating the cost logic are illustrated in **Equation 3** and **Equation 4**, however the application of the profit margins is hidden for confidentiality purposes.

Table 15. *List of other revenue parameters used for the revenue model.*

Parameters	
In-House	
Regular order margin %	
Urgent order margin %	
One-time part order margin %	
% Regular orders	
% Urgent orders	
% One-time orders	
Repair discount price %	
Service Bureau	
Unit cost (as % of in-house production cost)	
% Regular orders	
% Urgent orders	
% One-time orders	

For prototype and repair parts:

Equation 3. *Subset of **Equation 1**: Set of cost and revenue equations for prototype and repair parts. Note that the cost equation is the same between the two applications, but the revenue equations differ.*

$$\boldsymbol{COST\ for\ APPLICATION}\ [€/\boldsymbol{yr}] = yearly\ qty\ of\ orders\ (within\ capacity) \times (fixed\ costs + material\ costs + \%\ space\ occupied\ by\ order \times variable\ costs)$$

$$\boldsymbol{Fixed\ costs} = software\ cost + finishing\ cost + shipping\ cost + dyeing\ machine\ cost + vapor\ smoothing\ machine\ cost$$

$$\boldsymbol{Material\ costs} = qty\ of\ parts\ per\ order \times part\ weight \times (1 + material\ loss\ per\ job) \times (material\ cost + cost\ of\ agent\ consumed\ by\ 1kg\ of\ material)$$

$$\%\ \boldsymbol{space\ occupied\ by\ order} = (qty\ of\ parts\ per\ order \times part\ volume) \div (avg\ part\ volume \times avg\ qty\ of\ parts\ per\ job)$$

$$\boldsymbol{Variable\ costs} = printing\ costs + manual\ unpack\ costs + sandblasting\ costs + dyeing\ costs + vapor\ smoothing\ costs$$

$$\boldsymbol{REVENUE\ for\ PROTOTYPE}\ [€/\boldsymbol{yr}] = yearly\ qty\ of\ orders\ (within\ capacity) \times [\ \text{application of margin to costs}\ ]$$

$$\boldsymbol{FC_{part\ I}} =$$

$$\boldsymbol{FC_{part\ II}} =$$

$$\boldsymbol{REVENUE\ for\ REPAIR}\ [€/\boldsymbol{yr}] = yearly\ qty\ of\ orders\ (within\ capacity) \times \left[\ \text{application of margin and discount to costs}\ \right]$$

$$\boldsymbol{FC_{part\ Ia}} =$$

$$\boldsymbol{FC_{part\ Ib}} =$$

$$\boldsymbol{FC_{part\ II}} =$$

For production parts:

Equation 4. *Set of cost and revenue equations for production parts.*

$$\boldsymbol{COST\ for\ PRODUCTION}\ [€/\boldsymbol{yr}] = yearly\ qty\ of\ orders\ (within\ capacity) \times (fixed\ costs + material\ costs + qty\ of\ jobs\ needed\ to\ fulfill\ order \times variable\ cost)$$

$$\boldsymbol{Fixed\ costs} = software\ cost + shipping\ cost$$

$$\boldsymbol{Material\ costs} = qty\ of\ parts\ per\ order \times part\ weight \times (1 + material\ loss\ per\ job) \times (material\ cost + cost\ of\ agent\ consumed\ by\ 1kg\ of\ material)$$

$$\boldsymbol{Qty\ of\ jobs\ needed\ to\ fulfill\ order} = (qty\ of\ parts\ per\ order \div ROUNDUP((build\ unit\ volume \times material\ density \times packing\ density) \div part\ weight)$$

$$\boldsymbol{Variable\ costs} = printing\ costs + manual\ unpack\ costs + sandblasting\ costs + dyeing\ costs + vapor\ smoothing\ costs + quality\ control\ costs$$

$$\boldsymbol{REVENUE\ for\ PRODUCTION}\ [€/\boldsymbol{yr}] = \text{application of margin to costs}$$

Finally, for the environmental footprint model, the various consumption and waste quantity data were provided by recent experiments performed by the Add Lab, as shared earlier. Note that the transportation of power and agent from the supplier to Add Lab was excluded since the measurements from the team demonstrated its negligible impact. The EF scores were sourced from the EF database accessible through Decathlon. **Table 16** below shows the parameters considered in this model, and **Equation 5** shows the actual calculations to compute an EF score per part.

__Table 16.__ List of process inputs and outputs, EF scores from Glimpact database, and other key parameters used for the environmental footprint model.

Input & Output Inventory	Value	Units
Material use	Mass of part x material loss	kg/kg part printed
Waste material (recycling)	2	kg/kg part printed
Waste material (incineration)	0.1	kg/kg part printed
Agent use	0.05	kg/kg part printed
Sandblasting media use	1	kg/kg part printed
Waste sandblasting media	1	kg/kg part printed
Printer energy consumption	45	kWh/kg part printed
Sandblasting energy consumption	0.4	kWh/kg part printed
Dyeing energy consumption	4	kWh/kg part printed
Vapor smoothing energy consumption	0.4	kWh/kg part printed
Keyence energy consumption	0.4	kWh/kg part printed
Sandblasting compressed air consumption	5	m3/kg part printed
Transportation to service bureau	50	km/kg part printed

EF Single Score (from Glimpact)	Value	Units
Material production	700	/kg
Agent production	500	/kg
Sandblasting media production	85	/kg
Plastic recycling, pelletization	12	/kg
Plastic incineration	17	/kg
Glass incineration	12	/kg
Plastic landfill	3.7	/kg
Electricity mix	25	/kWh
Compressed air	1.3	/kg
Freight, lorry	10	/kmton

Other Parameters	Value	Units
Material powder density	0.5	g/cm3
Material fused powder density	1	g/cm3
Material loss per job	20	%
Process yield	93	%

__Equation 5.__ Adaptation from __Equation 2__: Set of EF score per part calculations.

$$\boldsymbol{EF\ score\ per\ part} = \left[EF\ score_{material} + EF\ score_{agent} + EF\ score_{media} + EF\ score_{electricity} + EF\ score_{compressed\ air} + EF\ score_{tranportation}\right] \div annual\ demand\ of\ parts$$

$$\mathbf{DQ} = yearly\ demand\ mass\left(\frac{kg}{yr}\right) = \begin{bmatrix} prototype\ demand\left(\frac{parts}{yr}\right) x\ mass\ of\ prototype\ part\ (kg) \\ +aftersales\ repair\ demand\left(\frac{parts}{yr}\right)\ x\ mass\ of\ aftersales\ repair\ part\ (kg) \\ +production\ demand\left(\frac{parts}{yr}\right)\ x\ mass\ of\ production\ part\ (kg) \end{bmatrix}$$

$$\boldsymbol{M} = \ mass\ of\ printed\ parts\ in\ a\ job\left(\frac{kg}{job}\right) = mass\ of\ powder\ in\ BU\left(\frac{kg}{job}\right)\ x\ packing\ density\ (\%)$$

$$\boldsymbol{Y} = process\ yield\ (\%) = percent\ successful\ parts\ in\ a\ job$$

$$\boldsymbol{EF\ score_{material}} = DQ\ x\left(\frac{1}{M}\right)x \begin{bmatrix} mass\ of\ powder\ in\ BU\left(\frac{kg}{job}\right)x\ material\ loss\ per\ job\ (\%)\ x\ EF\ score_{material\ production} \\ +mass\ of\ waste\ powder\left(\frac{kg}{job}\right)\ x\ EF\ score_{plastic\ incineration-landfill} \\ +mass\ of\ unused\ reclaimed\ powder\left(\frac{kg}{job}\right)\ x\ EF\ score_{recycling} \end{bmatrix} \div Y$$

$$\boldsymbol{EF\ score_{agent}} = DQ\ x\left(\frac{1}{M}\right)x\ \left[mass\ of\ agent\ consumed\ in\ a\ job\left(\frac{kg}{job}\right)\ x\ EF\ score_{agent\ production}\right] \div Y$$

$$\boldsymbol{EF\ score_{sandblasting\ media}} = DQ\ x\left(\frac{1}{M}\right)x \begin{bmatrix} mass\ of\ media\ consumed\ in\ a\ job\left(\frac{kg}{job}\right)\ x\ EF\ score_{agent\ production} \\ +mass\ waste\ media\left(\frac{kg}{job}\right)\ xEF\ score_{glass\ incineration\ -landfill} \end{bmatrix}$$

$$\boldsymbol{EF\ score_{electricity}} = DQ\ x\left(\tfrac{1}{M}\right)x\ \left[(printer\ electricity\ consumption + sandblasting\ electricity\ consumption)\ \left(\tfrac{kWh}{job}\right)\ x\ EF\ score_{electricity\ mix}\right] \div Y$$

$$\boldsymbol{EF\ score_{compressed\ air}} = DQ\ x\left(\frac{1}{M}\right)x\ \left[compressed\ air\ used\left(\frac{kg}{job}\right)\ x\ EF\ score_{compressed\ air}\right]$$

$$\boldsymbol{EF\ score_{transportation}} = DQ\ x\ \left[(distance\ to\ service\ bureau\ (km)\ x\ EF\ score_{ground\ freight}\right]\ --\ only\ for\ service\ bureau$$

5.2.3. Derived Parameters

Some important projections need to be modeled and quantified in order to run this flexibility analysis. As discussed in the problem statement, uncertainties come from future demand and the upcoming technological improvements initiated by suppliers.

To model the yearly demand projection, the estimates provided for the next ten years were plotted and interpolated using the trendline function in Excel. A linear trendline was used for production parts as the demand is projected to grow continuously as the technology develops and the scale of applications and product types expands. A logarithmic trendline was used for prototype parts since this application is in a slight growth stage that will soon reach a stabilization phase since it depends on the number of designers and product engineers in the company rather than market demand. For repair parts, a polynomial trendline was used to match the current ramp-up in demand the application faces and the eventual stabilization of this demand. **Figure 56** shows the increase in demand volume over the 10-year time frame for each application. Note that the production demand is orders of magnitude larger than prototype and after-sales repair part volumes.

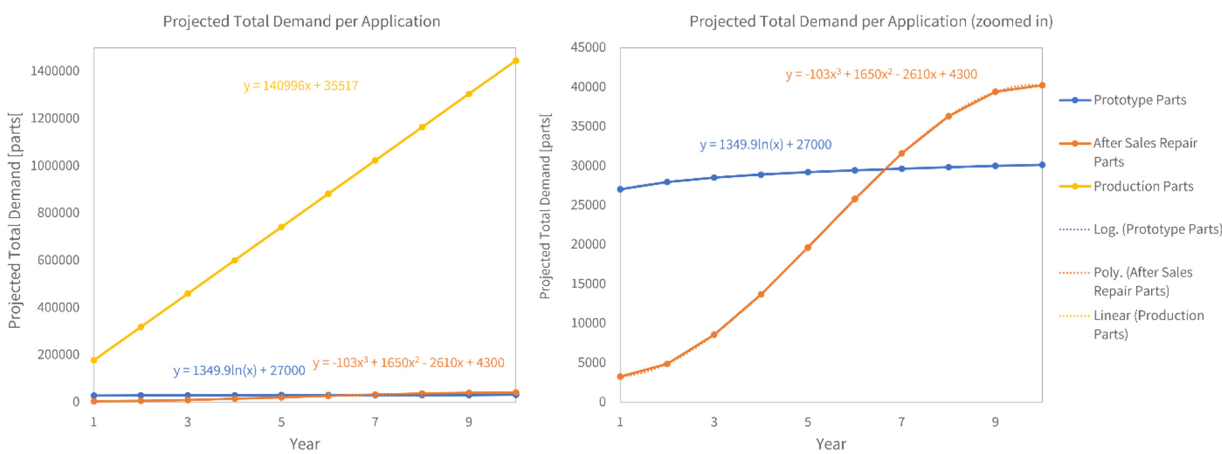

Figure 56. Projected yearly demand volume per application based on Decathlon estimations.

The modeling of the technological progress was done for two areas: improvements in material sustainability and improvements in printer efficiency. In both cases, the improvements were modeled in such a way that they happened simultaneously as if corresponding to the launch of a new, more performant product (material or printer), resulting in one cost change. The year of "release" was decided to be years 2 and 6 both on the materials and printer sides. This decision was made based on the knowledge that more sustainable material options are already available now, and many 3D manufacturers are increasingly pressured to improve the environmental impact of their machines. Additionally, it is fair to assume that 3D materials and printers are complementary technologies [54], [186] and their development will occur somehow simultaneously.

The parameters impacted by the advancement in material sustainability were narrowed down to environmental footprint, material loss per job, and the associated cost of the new material. The exact growth numbers defined in the model are not validated and are used as placeholders until more information is available. The projections can be found in **Figure 57**.

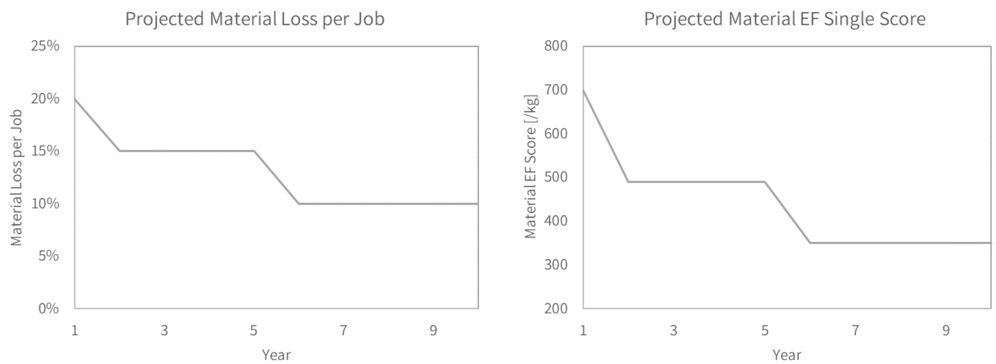

Figure 57. *Projection of improvement in material performance based on the percent material lost per job and the EF single cost of the material.*

The progress projection for the 3D printers was modeled arbitrarily. It represents a convolution of design improvements and a natural learning curve from the user, who will identify how to use the machine most efficiently. The parameters tracked for progress include process yield, number of jobs per day per printer, and printer energy consumption, the latter resulting from faster print speed or better component design. **Figure 58** below shows the evolution of these metrics over the duration modeled.

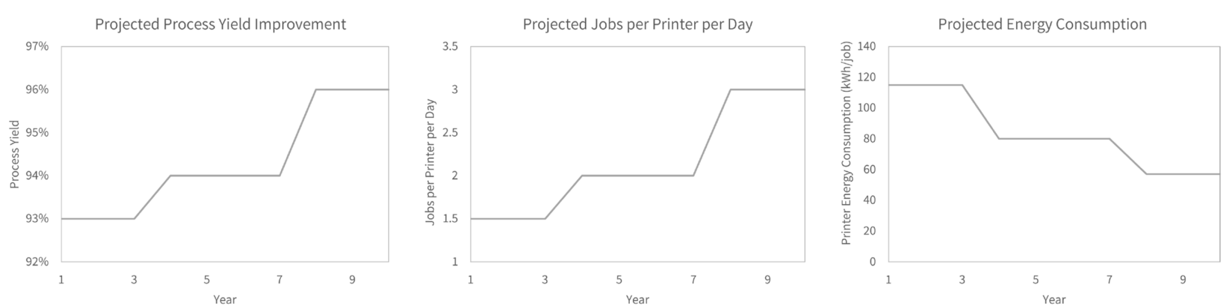

Figure 58. *Projection of improvement in printer performance based on the process yield, number of jobs per printer per day, and the energy consumption per job.*

5.2.4. <u>Uncertain Parameters</u>

*(**Figure 16** process step: Step 4 "Uncertainty")*

All the parameters mentioned thus far are based on averages and projections. However, many of them realistically should be considered as probabilistic distributions rather than static numbers. Only four predominant uncertainties were selected and incorporated in the model as distribution to take these flawed inputs into account without drastically increasing the complexity of this model. The selection was focused on uncertainties related to the demand and technological improvement projections. It also only included factors that impact both cost and EF (i.e., average order quantity was excluded as it only impacts costs). The 3D printing process parameters contain many variables that are based on averages as well and would be worth investigating in future flexibility analysis work.

These new non-static inputs are fed through a Monte Carlo simulation to produce a more representative output of the system's financial and environmental performance. A description of the three uncertainties is provided below:

Demand Projection Uncertainties:

1. **Yearly demand volume** – This parameter represents the number of unique products ordered over a year in the Add Lab. It is an uncertainty for each application in different ways. Starting with prototypes, the overall quantity of orders should not change much, given that the demand is proportional to the number of design teams in the company. However, the mix between the three materials considered in the model will vary as PA11 becomes available. However, the overall capacity will not change meaning that the demand for PA12 and TPU might need to go down. The new product demand represents the largest uncertainty because of the risks associated with developing a brand-new product at scale and the market uncertainty due to estimated customer adoption. Finally, the repair component demand will also be uncertain since this application is new, and the availability, communication, and operation around part repairs is still being developed. This uncertainty will, therefore, be considered for each product option modeled.

2. **Average part size** – The size of parts will vary greatly across products, given their different designs and geometry. The range of part sizes that can be 3D printed varies between less than 5 grams to 150 grams. However, in this model, the parameter represents a yearly average, meaning that the variability from year to year will not be as wide as 5 grams to 150 grams but rather follow a more uniform distribution.

Technological Improvement Projection Uncertainties:

3. **Year of material and printer releases** – The year in which more sustainable materials will be released has some uncertainty, given that the supplier might be delayed in its R&D work to improve the material production process. Similarly, the release of a new printer might be delayed due to product development work being behind schedule or being released earlier if, for some reason, it has become a priority for the 3D printer

manufacturer to improve the efficiency of its product. For simplicity, the material and printer release uncertainties will be tied together.

In order to include these uncertainties in the model calculations, each uncertainty was attributed a probability distribution. The following table describes the distribution ranges chosen and the reasoning behind each assumption. **Figure 59**, **Figure 60**, and **Figure 61** illustrate the distribution shape of these uncertain parameters.

Table 17. Summary of uncertainty variables and their respective ranges of values.

Uncertain Parameter	Expected Value	Low Value	High Value	Distribution Shape	Rationale
Prototype Part Demand Volume	27000 + projection	-10%	10%	Uniform	The demand is very uncertain across all applications, however, since the prototype business has been around for a long time, the predictions around it are more reliable than for after-sales repair parts or production parts, hence the 10 versus 25% distribution range.
After-Sales Repair Part Demand Volume	3000 + projection	-25%	25%		
Production Part Demand Volume	175000 + projection	-25%	25%		
Prototype Average Part Size	35	28	42	Uniform	This number is a yearly average, therefore the changes from year to year should be small compared to changes in part size at the individual part label (ranging from 1 to 150 grams for any application). This yearly data is driven by the types of products that are 3D printed, which can be very variable in a sporting goods company. Based on historical data on after-sales parts, a variation of about 20% was observed from year to year. The same variation was applied to prototypes given the similar nature, and a slightly larger percentage was applied to production parts.
After-Sales Repair Average Part Size	50	40	60		
Production Average Part Size	5	3	7		
Year of Material & Printer Release #1	2	2	4	Triangular	The variation in new material or printer release year is very arbitrary. To guide the assumptions made, a triangular distribution was chosen to reflect the lower potential for new releases to happen earlier than the projection and higher potential for them to happen past the projected year..
Year of Material & Printer Release #2	6	5	9		

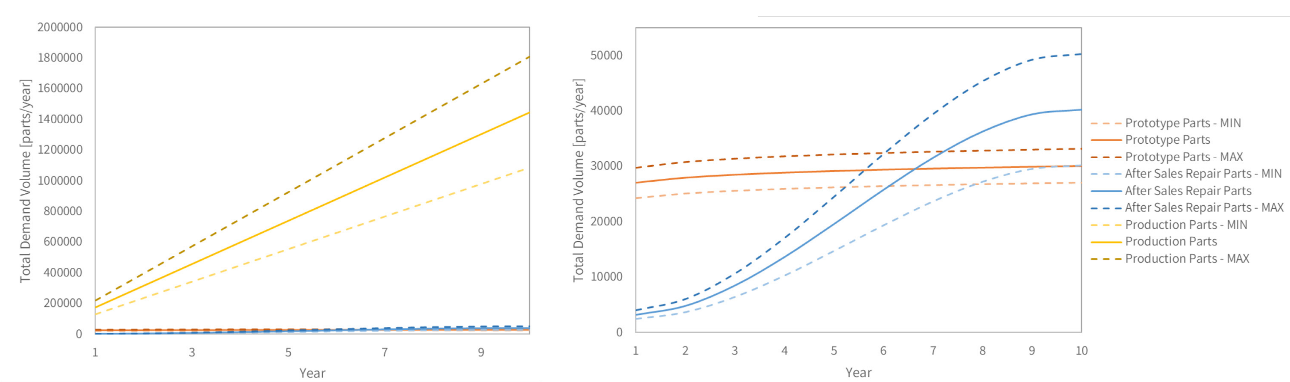

Figure 59. Projected demand for each application with uniform uncertainty band highlighted in dashed lines.

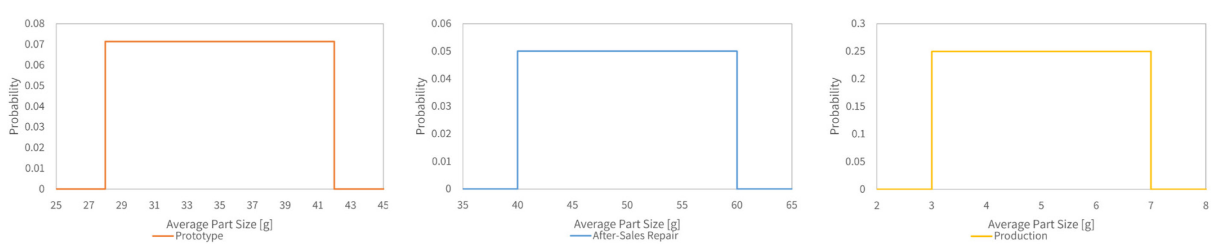

Figure 60. Uniform probability distribution for the average part size of each application.

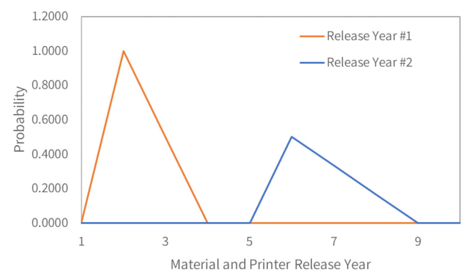

Figure 61. Triangular probability distribution for the new material and new printer release dates.

5.2.5. Key Model Decisions

(Figure 16 process step: Step 5 "Decisions")

This process step consists of identifying the decisions the Add Lab will need to take throughout this analysis timeline. Based on the strategic questions of the Add Lab team that are driving this analysis' objectives, this model will explore three decision areas:

1. **Decision Set #1:** Should Add Lab rent a larger facility? If yes, when should Add Lab move operations to the new facility, and which variables should be a trigger for this move?
   Related Question (#3a): Should Add Lab consider expanding its capacity to support the growing demand in-house or continue leveraging service bureaus to handle any additional demand as they do today?
   Motivation: This question drives the primary decisions of this analysis. The decision to expand is interesting for the team since it would allow the purchase of additional printers to increase their production volume, triggering the question of when a good time would be to leverage this additional capacity. These decisions would contribute to Decathlon's goals to reduce by 90% scope 1 and scope 2 emissions, as well as use 100% renewable energy for its sites. In fact, this scenario would provide Add Lab with more control over its resources and their environmental quality.

2. **Decision Set #2:** At what point should Add Lab invest in the co-development of more sustainable materials with its material suppliers by suggesting and financing better sustainable practices or testing new materials offered by the supplier, AND invest in the co-development of more efficient printers with 3D printer manufacturers (HP) by being an engaged testing partner?
   Related Question (#2): Is it worth incentivizing suppliers through investments such as co-development efforts? What event should justify the investment?
   Motivation: This decision relates to the influence Decathlon might exert on its suppliers and potential incentives the company could put in place to accelerate the development of cleaner materials and more efficient printers. Co-development is a common way for additive manufacturing players to accelerate the development of the technology, as

shown through the partnerships between HP, Sandvik (material supplier), and Endeavor 3D (service bureau) [187] or through the recycling project Decathlon and Arkema have been collaborating on. It represents a resource investment now to ensure a better quality in the future. These two decisions could be applied to any expansion scenario, although their impact might differ. These actions would be in line with the science-based target of 90% of suppliers setting SBT by 2026 and would contribute to the 53% emission intensity reduction for scope, 1, 2, and 3.

3. **Decision Set #3:** Should Add Lab invest in greener sources of energy to supply electricity to Add Lab's facility? What type of alternative would be most effective?
   Related Question (#4): Should Add Lab upgrade its facility energy source to meet environmental goals? Is the investment worth the environmental gain?
   Motivation: The current facility is not suited for installing solar panels. An improvement option would be to switch their utility contract to a greener energy mix. This option would be available in any facility expansion scenario. The decision to rent a new facility, however, opens the door to other options for greener energy sourcing. By moving, the Add Lab now has the option to invest in behind-the-meter power generation equipment, such as solar panels. This decision supports Decathlon's objective to source electricity from 100% renewable energy for all of its stores, warehouses, and supplier buildings. It would also reduce the emissions for scope 1 and 2.

In the base case scenario, representing the current setup of the Add Lab, it is assumed that the answer will be no to all these decisions and Add Lab will stay the course of leveraging service bureaus, benefiting from the technological improvements when they occur, and maintaining its energy source as is. The appearance of these decisions will come in the flexibility analysis after understanding the performance of the base case scenario. The goal of this analysis is to help the Add Lab team evaluate tradeoffs between the various decision options and guide strategic decision-making in a way that considers multiple sources of uncertainty.

5.2.6. Other Model Assumptions

It is important to note some of the other key assumptions that were made in this model.

Regarding the parameters used to characterize the 3D printing process and the capacity of the Add Lab, it was assumed that all the machines in the Lab have a life of four years and their replacement does not disrupt the yearly production volume. This assumption impacts the cash flow model as new equipment will be purchased every four years, and the unit cost will consider a 4-year amortization. For this model, it was assumed that Add Lab already has equipment purchased that will be functional for the next four years. Within the capacity model, the decision process to outsource an order to a service bureau was also simplified by assuming that Add Lab would fulfill prototypes first, then fill the remainder of the capacity with after-sales repair parts first, then take on as much of the production runs as they could and outsource the rest. If after-sales repair parts are outsourced, it was assumed that the overhead cost would be 25% of the one for production orders, and the quality control duration would take 30 minutes rather than 3 hours due to the much lower quantity of parts per order.

Assumptions were made when modeling the technological improvement projections as well. Each material and printer release are associated with a cost increase of 10%. For example, when material suppliers release material with a 15% powder loss per job and an EF score of 490 rather than 700, the cost of material per kilogram will go up by 10%. It was assumed that the lifespan of a printer would remain the same despite these efficiency improvements.

Regarding the decisions explored, the scenario of moving to a new facility was bound and simplified using three major assumptions. First, the new facility will have the capacity for 4 printers in total. Second, the new facility will have 2x the footprint of the current facility. And third, it will be the same leasing cost per square meter for both the current and the new facility.

Finally, a discount rate of 10% was chosen for this analysis since the project is at the intersection between stability from existing operations and success, and high uncertainty based on the demand for this still-developing technology.

All assumptions were made in an attempt to simplify the model and some of the complexity associated with the representation of this particular system, knowing that they could represent limitations to the analysis.

5.3. Base Case

*(**Figure 16** process step: Step 6 "Model")*

With the system model now defined, the analysis of flexible decisions and scenarios can start. However, it is important to establish a reference point based on static values before exploring flexible options and the impact of uncertainties. The base case will serve as that and reflect the current Add Lab situation.

5.3.1. Static Base Case

As described above, the current Add Lab situation consists of an in-house capacity of two printers, the leverage of service bureau outsourcing as capacity is exceeded, and a fixed facility footprint. The two printers are upgraded every four years, assuming the latest technological improvements as projected. Even if an improved printer is available before the 4-year mark, the benefits will only be taken into consideration once a new printer needs to be purchased. On the other hand, material parameters are updated as soon as new releases are available since material change is a simple process for 3D printing. Uncertain parameters are not considered, and the current projections of demand and technological advancements are modeled as if they were going to be perfect predictions. The model calculations and outputs for the static case are shown in **Appendix A Figure 78**.

The static base case analysis results in a positive NPV value of €0.20M and an EF score per part of 14.6, values which will serve as reference points to the following analyses considering uncertainty and flexible options.

5.3.2. Base Case with Uncertainty

Before implementing the uncertainty factors identified earlier, it is important to understand their relative impact on the system's performance. To do so, each uncertainty variable identified in **Table 17** was increased or decreased, one at a time, to understand their individual impact on the model outputs. The change in variable value was based on the distribution curve assigned to the parameters and the choice of a realistic standard deviation (in %). A tornado diagram for each system performance metric was built to assess the deviation from the static base case performance caused by each parameter, as shown in **Figure 62** and **Figure 63**. The high uncertainty values in orange represent the increased state of the variable (e.g., +10% of prototype demand volume), while the low uncertainty values in blue represent the decreased state of the variable (e.g., -10% of the prototype demand volume).

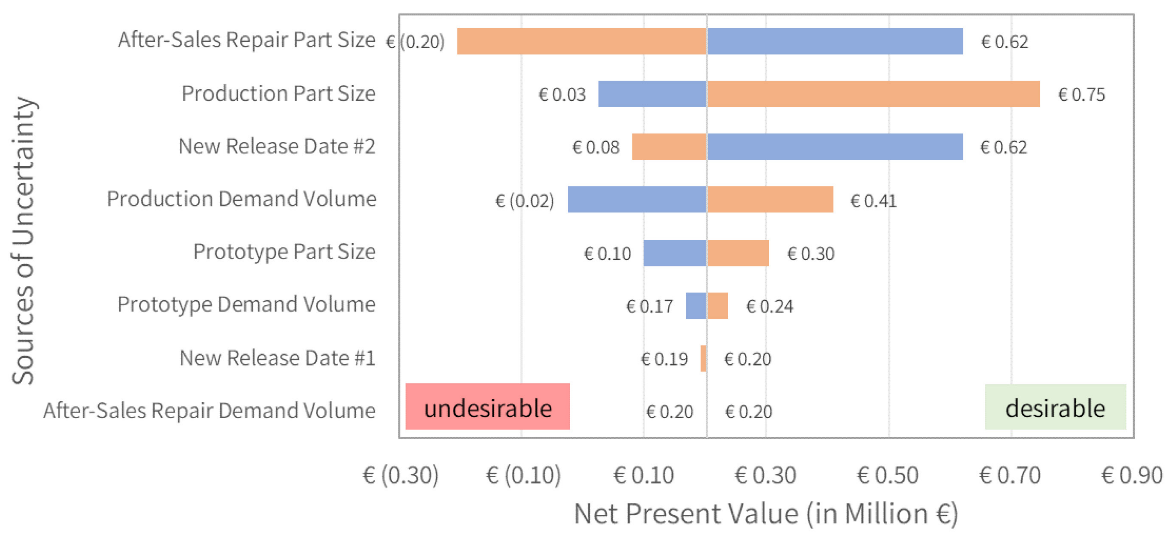

Figure 62. *Tornado diagram representing the sensitivity of NPV to major sources of uncertainty. The blue bars represent the performance with the low uncertainty values, and the orange bars represent the performance with the high uncertainty values.*

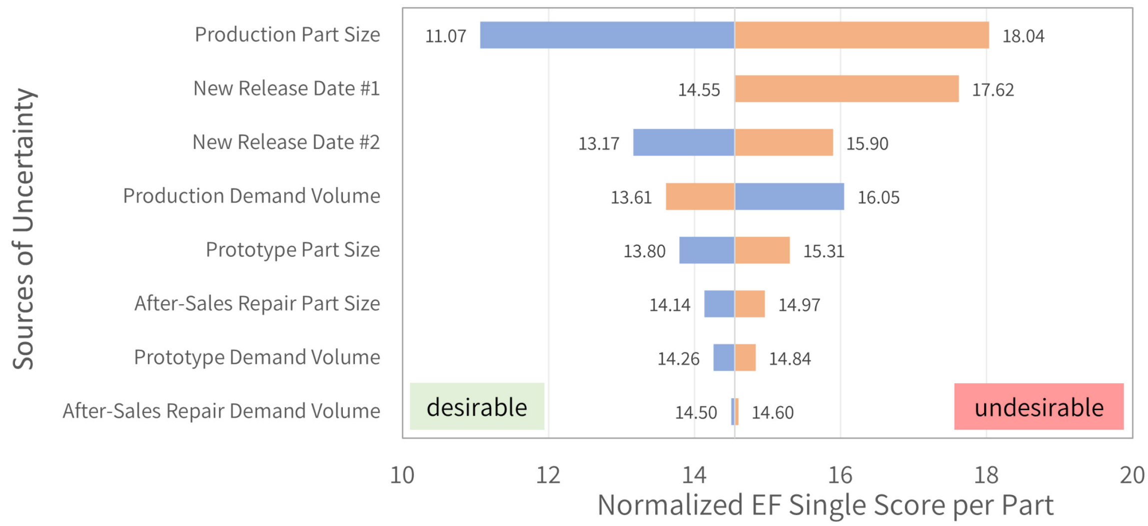

Figure 63. *Tornado diagram representing the sensitivity of the normalized environmental footprint metric to major sources of uncertainty. The blue bars represent the performance with the low uncertainty values, and the orange bars represent the performance with the high uncertainty values.*

The tornado diagrams show an asymmetric response for many of the parameters. This is due to the non-linear relationship between performance (NPV or EF) and input variables. The various types of applications and the in-house capacity limit are examples of factors affecting this non-linearity since they create a non-uniform system. On the NPV side, the part size of prototype and production applications seems to be a major sensitivity. On the EF side, the production part size and the new technology release dates show the most substantial impact. Moreover, it is important to note the opposing forces observed between both performance metrics. As production or prototype part size increases, for example, the NPV increases (desired behavior), but EF per part increases as well (undesirable behavior). On the other hand, the after-sales repair part size has a desirable impact on both NPV and EF as it goes down. Factors with an opposite impact on NPV and EF need to be balanced for optimal results. Another interesting observation lies in the opposite impact of the different applications. For example, an increasing production part volume leads to a lower EF score, but an increasing prototype or after-sales repair part volume increases the EF score. This could be explained by the impact of part size on the EF score seen in the tradespace analysis: production parts have a much smaller average size compared to the other applications, and it was concluded that smaller part sizes reduce the EF score. On the cost side, higher after-sales repair part size and volume lead to a lower NPV, while higher prototype and production part size and volume lead to a higher NPV. This behavior stems from the profit loss caused by after-sales repair parts given the discount price offered for consumer incentives.

The figures below illustrate an example of the simulated "realized" demand and technological progress (solid lines) compared to the projections (dashed lines) once implemented into the model. The demand and part size realized values, being uniformly distributed around the projected value, show variance, but if simulated many times, the average would be equal to the projection.

Figure 64. Realization of the demand projection based on the uncertainty ranges defined in Table 17.

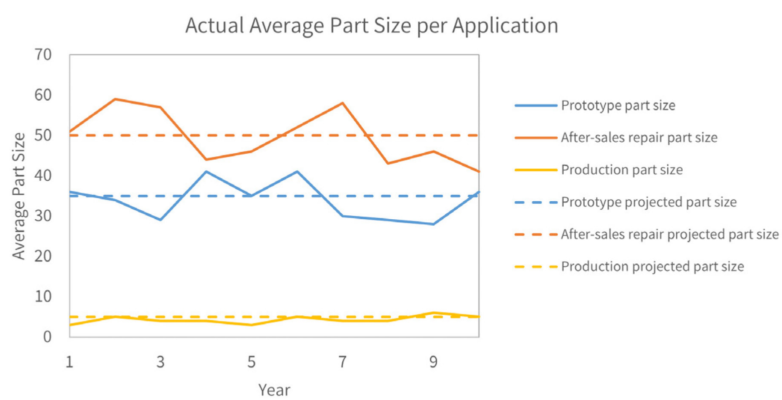

Figure 65. Realization of the average part size projection based on the uncertainty ranges defined in Table 17.

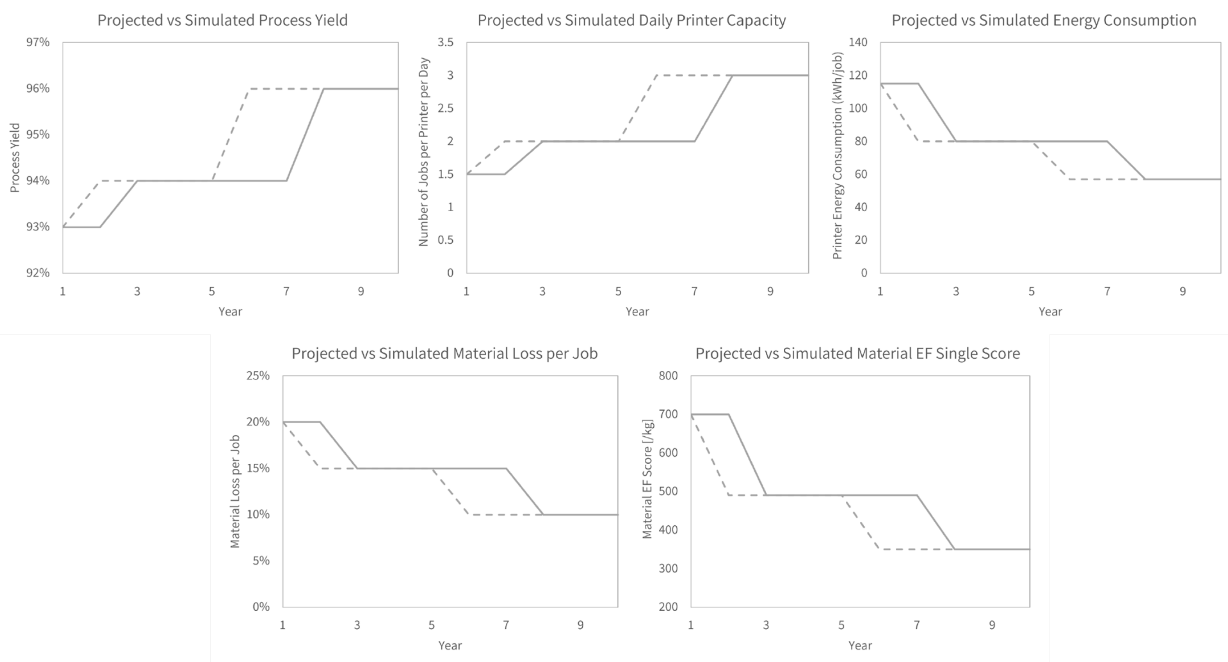

Figure 66. Realization of the new material and printer release date projections based on the uncertainty ranges defined in Table 17.

Implementing these uncertainties into the model results in a randomized version of the static base case, as **Appendix A Figure 79** shows. This model can now be simulated 2000 times in a Monte Carlo simulation to obtain a probabilistic distribution of the net present value and the environmental footprint per part, as shown in **Figure 67** and **Figure 68**, respectively. For the NPV, the average of the base case's performance curve with uncertainty almost perfectly aligns with the determinist NPV, meaning that factoring in uncertainty results in a similar expected average performance (€0.22M versus €0.20M). However, the uncertainty of the model inputs yields a wide distribution of the performance curve, showing a low tail reaching a minimum of €(0.40)M and a high tail reaching €0.82M. This result shows that there are downsides the system should be shielded from and upsides for the system to capture. The observations are slightly different on the EF score per part because the average EF score performance considering uncertainties is lower than the deterministic average EF per part (13.80 versus 14.6). The EF distribution curve also has a large spread and is almost uniformly distributed along the performance range (seen by the linear cumulative curve). The cause of this behavior is not clear and deserves more investigation. In general, two opposing forces were observed: (1) since prototypes and after-sales parts are larger parts and occupy a larger part of the in-house capacity, the denominator of the EF per part score is smaller, increasing the average EF performance of the in-house production, and (2) wherever more production parts are produced, the EF score lowers due to the phenomenon observed in the uncertainty sensitivity analysis and the fact that production part volumes are order of magnitudes larger than prototype and after-sales repair applications.

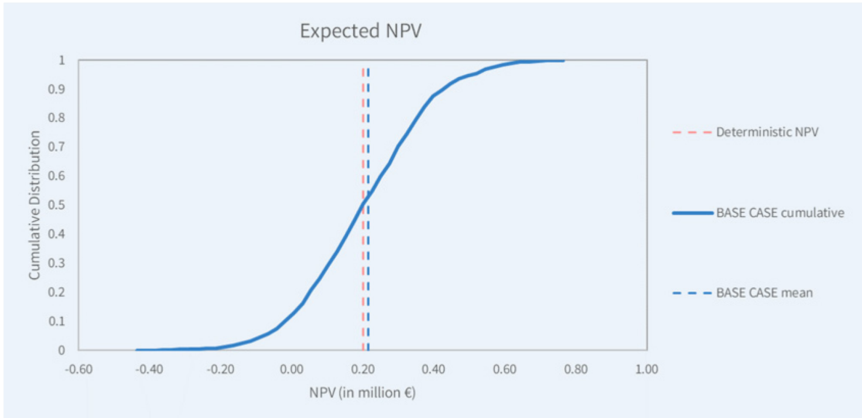

Figure 67. *NPV target curve for the base case with uncertainty, including sources of uncertainty based on 2000 simulation runs. The deterministic NPV without uncertainty is shown in the red line.*

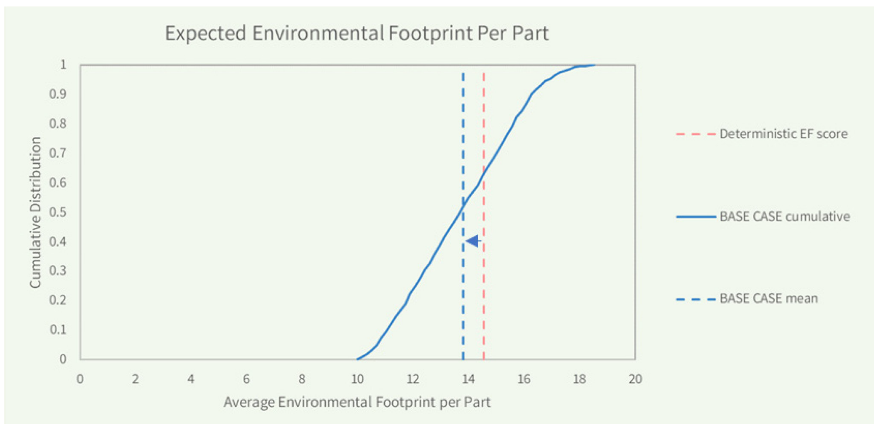

Figure 68. *EF score target curve for the base case with uncertainty, including sources of uncertainty based on 2000 simulation runs. The deterministic EF score per part without uncertainty is shown in the red line.*

Table 18. *Multi-dimensional performance of the base case design with uncertainties.*

Dimensions	Base Case
Average NPV	**€ 0.22M (vs € 0.20M)**
Std dev NPV	81.76%
Min NPV	€ (0.40)M
Max NPV	€ 0.82M
Average EF per part	**13.80 (vs 14.6)**
Std dev EF per part	14.19%
Min EF per part	9.89
Max EF per part	17.96

5.4. Incorporating Flexibility

Now that the impact of uncertainty on the NPV and EF performance of the base case is understood and has shown the probability of facing risks and opportunities, the design of flexible options can begin. The objective of this analysis is to compare these results with the performance of other flexible options and see if a scenario is more optimal at maximizing the upsides and minimizing the downsides for both NPV and EF performance.

5.4.1. Flexibility Levers

*(**Figure 16** process step: Step 7 "Flexibility")*

To address the uncertainty sources shown in the tornado diagrams and compare different investment strategies, the levers shown in **Table 19** are implemented in the model and compared to the base case scenario and each other.

Table 19. *Summary of implemented flexibility actions for Add Lab growth strategy.*

Decision Set	Flexibility Action	Rationale	Model Implementation	Effect of Action
#1: Expanding capacity through facility rental	Conditional move to the new facility based on demand trends	A new space is rented upfront and is available to move operations when is most ideal based on the updated demand projection. The team can plan for the move in the meantime so that the transfer can happen quickly. This short move timeframe allows more confidence in demand projection since it will be for a year out.	IF(total demand for parts in 'printers needed' units >= 4) → buy 2 more printers and move operations to new facility ELSE → keep operating the 2 printers in current facility and renting the space	*Maximize Upside and Minimize Downside (NPV):* allows a reduction of upfront costs and increases production when needed.
#2: Investment in co-development with material and printer supplier	Conditional investment in the co-development of greener materials and more efficient printers based on status of release in year 2	As a buyer, Decathlon has an influence on its suppliers and could accelerate and engage in the development of more sustainable materials. The flexibility lies in Add Lab being able to wait and see if the new material release occurs on its own before deciding to invest in the supplier's R&D efforts and guaranteeing availability sooner.	IF(material loss/energy consumption in Year 2 isn't lower than Year 1) → invest €20,000 in co-development in Year 2 to guarantee new material release in Year 3 and faster second release ELSE → don't invest because progress is happening already	*Maximize Upside (EF) and Minimize Downside (NPV):* A push is only done on the material and printer manufacturer if they do not deliver in the second year, minimizing unnecessary upfront costs and maximizing the availability of more energy-efficient options.
#3: Energy sourcing alternatives	None. Only yes or no scenario.	Looking to see the impact of the most ideal scenario on each of the expansion cases.	/	/

The first condition considers purchasing 2 additional printers and moving to a new facility only when the demand to meet that capacity is projected for the following year. This is contingent on Add Lab renting the new facility from the start. The second condition is a simplified supplier incentive practice where, if the release of new materials or printers is not happening quickly enough, Decathlon can fast-track the development of new materials and printers by directly investing in the supplier's R&D work or by engaging its own resources to co-develop the projects with the supplier. As mentioned before, this assumption is not unrealistic since 3D printer manufacturers often partner with customers to accelerate the learnings on issue resolutions and process improvements, and material suppliers have a stake in working with their customers to receive feedback on material transferring and recycling practices to better share the knowledge and adoption. These conditions are later referred to as the "supplier incentives" options and are applied simultaneously when exercised. The investment for the material and printer development work is €10,000 each, and if made, guarantees the first release to occur in year 3 and the second between years 4 and 6, rather than between years 5 and 9. These assumptions may not be aggressive and representative enough and could be optimized in future work.

5.4.2. Flexibility Cases

*(**Figure 16** process step: Step 8 "Analysis")*

In order to draw a good comparison between these flexibility levers and the base case, another, more rigid scenario was modeled. This scenario consists of renting a new facility and moving in immediately with four printers, enabling the fulfillment of more demand in-house and the direct implementation of renewable energy generation equipment. With this additional scenario, three designs – the "base case" with no rent, the "rent and move", and the "rent and wait" – constitute the foundation of the flexibility analysis. On top of this comparison, given that the incentives to suppliers (push for greener materials and push for more efficient printers) could happen regardless of the facility expansion strategy, a with and without incentive comparison is evaluated. To guide the third decision of whether to invest in greener energy sourcing, an analysis on the opportunity to switch energy sourcing based on the expansion decision will also be compared between the three main designs (excluding the supplier incentives). As a reminder, this will consist of switching to a renewable electricity utility contract for the base case and installing solar panels for the renting cases.

The cases modeled, simulated, and compared are the following:

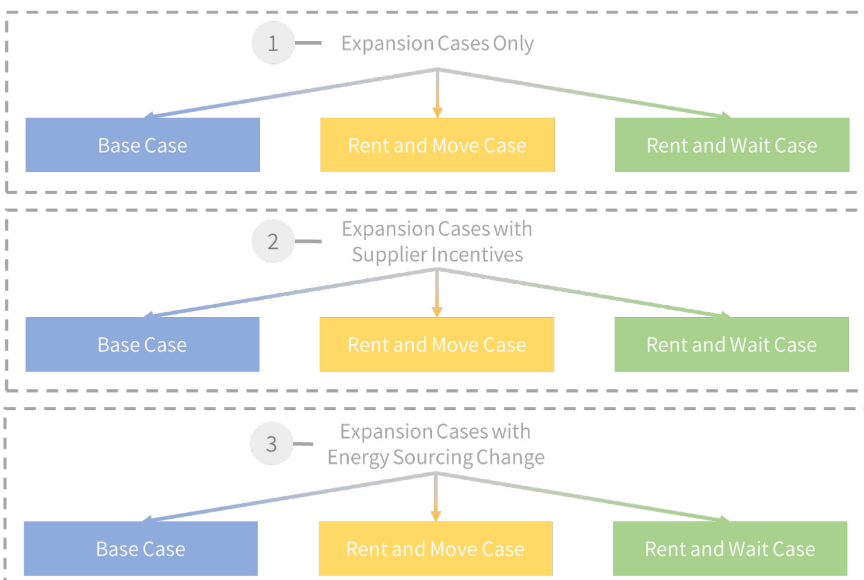

Figure 69. *Sequence of analysis to compare the three flexibility scenarios.*

5.4.3. Expansion Cases

The following analysis focuses on the base comparison between the three main expansion strategies.

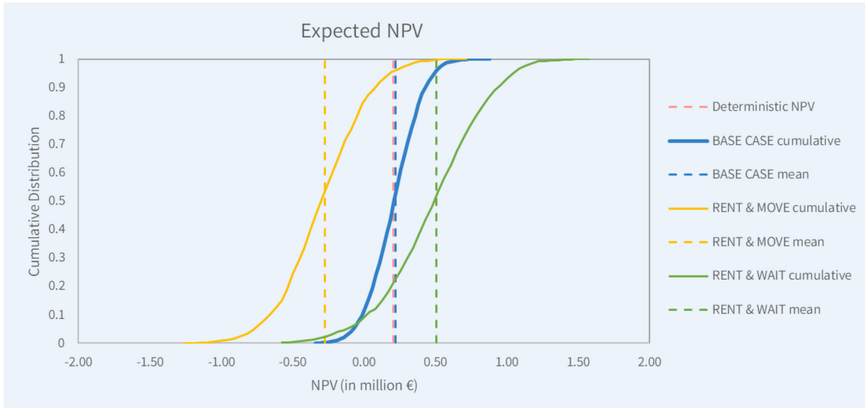

Figure 70. *NPV target curve for each expansion case.*

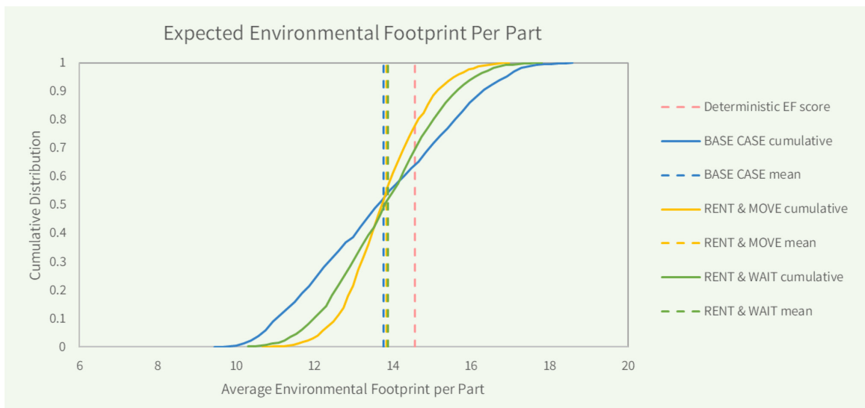

Figure 71. *EF score target curve for each expansion case.*

Table 20. *Multi-dimensional comparison of the three expansion cases.*

Dimensions	Base Case	Rent & Move	Rent & Wait
Average NPV	€ 0.22	€ (0.26)	€ 0.51
Std dev NPV	79.78%	110.28%	70.93%
Min NPV	€ (0.36)	€ (1.18)	€ (0.56)
Max NPV	€ 0.82	€ 0.90	€ 1.57
Average EF per part	13.7	13.82	13.78
Std dev EF per part	14.16%	7.53%	9.86%
Min EF per part	9.89	10.7	9.93
Max EF per part	19.16	18.16	18.95

The target curves in **Figure 70** and **Figure 71** and the multi-dimensional comparison in **Table 20** show that the Base Case scenario is more suited to reduce the low NPV results but limits the Add Lab's ability to grow its profit further. The Rent & Wait option offers the best performance in terms of average (132% higher NPV than Base Case), standard deviation, and max NPV and performs in between the Base Case and Rent & Move for the rest of the metrics. Rent & Move is the worst choice from an NPV perspective (218% lower NPV than the Base Case), but it slightly reduces the max EF score compared to the other designs. Based on this first analysis, the flexible option of Rent & Wait seems to provide a medium EF performance while enabling more considerable NPV gains with better control over the performance. In general, it is interesting to note that all NPV curves are normalized around their mean, even the Rent & Move scenario, where a larger downside was expected due to the upfront costs. On the EF side, all scenarios with uncertainty yield a lower EF score than the deterministic value, as already seen with the Base Case.

5.4.4. Expansion Cases & Supplier Incentives

This analysis focuses now on the impact of applying conditional incentives to material and printer suppliers simultaneously to accelerate the development of more sustainable materials and more efficient printers.

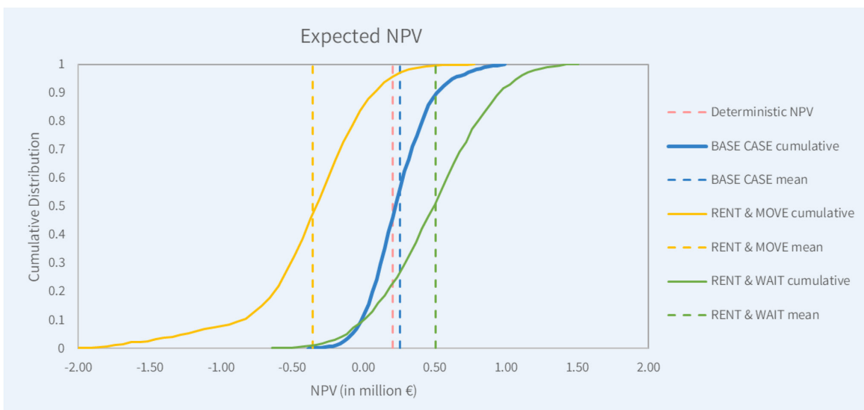

Figure 72. *NPV target curve for each expansion case considering supplier incentives.*

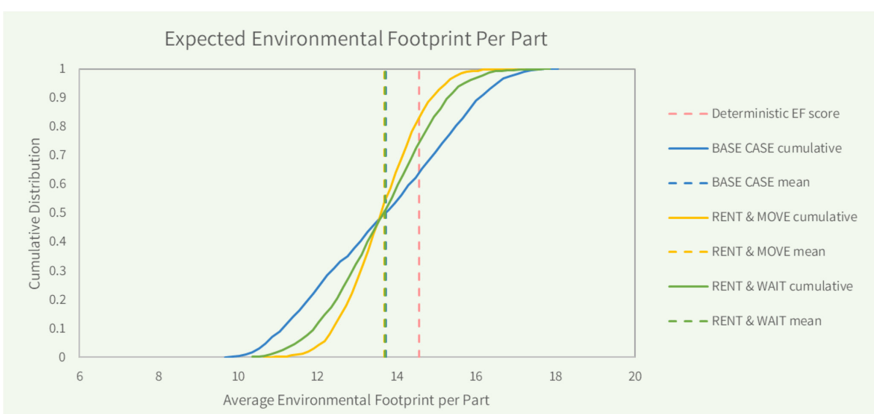

Figure 73. *EF score target curve for each expansion case considering supplier incentives.*

Table 21. Multi-dimensional comparison of the three expansion cases considering supplier incentives.

Dimensions	Base Case	Rent & Move	Rent & Wait
Average NPV	€ 0.26	€ (0.35)	€ 0.51
Std dev NPV	84.53%	118.43%	72.23%
Min NPV	€ (0.40)	€ (2.06)	€ (0.66)
Max NPV	€ 1.00	€ 0.80	€ 1.53
Average EF per part	13.73	13.69	13.71
Std dev EF per part	13.53%	6.99%	9.50%
Min EF per part	9.59	10.59	10.27
Max EF per part	18.14	17.48	17.93

When including the conditional incentives to material and printer suppliers to release improved products more quickly, the target curves shown in **Figure 72** and **Figure 73** barely move, the EF curve moving only so slightly towards a more desirable performance. The multi-dimensional comparison in **Table 21** reflects this observation. It shows that the Base Case scenario remains more suited to minimize the low NPV while the Rent & Wait option still offers the best performance in terms of average (96% higher NPV than Base Case), standard deviation, and max NPV. Rent & Wait, once again, performs in between the Base Case and Rent & Move for the rest of the metrics. Rent & Move appears to be the worst choice again from an NPV perspective (235% lower NPV than Base Case), but it still reduces the max EF score the most compared to the other designs. Based on this second analysis, Rent & Wait seems to still provide more control over the EF performance while potentially enabling larger NPV gains. The option to incentivize suppliers does not appear to be greatly beneficial to the EF performance in any scenario. This behavior might be due to the assumptions made in the design of this option and could be further tested with different input parameters. If realistic, however, these observations could lead to the conclusion that either more investment is needed to increase the environmental impact improvement of the technology (aligning with the concept of a “green premium”), or the cadence of technological improvement is occurring fast enough to capture the environmental benefits as early as possible with the current capacity scenarios.

5.4.5. Expansion Cases & Change in Energy Sourcing

For this analysis, several energy-sourcing changes are considered based on the capabilities of each design. The base case implements a switch to a greener energy mix from the utility provider (lower EF, high energy cost), and the two rent options model the installation of a renewable energy source, such as solar panels (upfront investment, much lower EF, and lower energy cost).

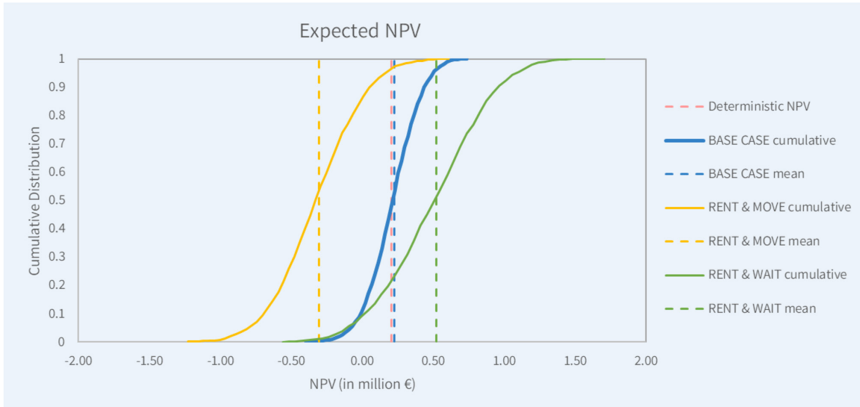

Figure 74. *NPV target curve for each expansion case considering alternative energy sourcing.*

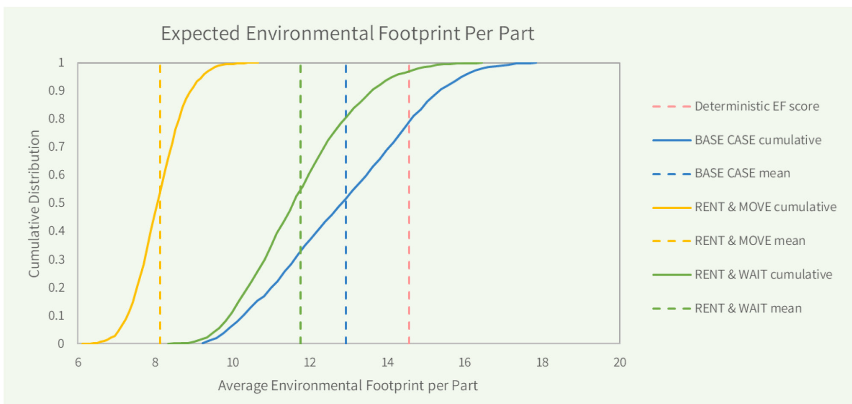

Figure 75. *EF score target curve for each expansion case considering alternative energy sourcing.*

Table 22. *Multi-dimensional comparison of the three expansion cases considering alternative energy sourcing.*

Dimensions	Base Case	Rent & Move	Rent & Wait
Average NPV	€ 0.22	€ (0.31)	€ 0.52
Std dev NPV	78.87%	95.46%	69.18%
Min NPV	€ (0.41)	€ (1.25)	€ (0.58)
Max NPV	€ 0.75	€ 0.63	€ 1.73
Average EF per part	12.84	8.1	11.75
Std dev EF per part	14.66%	8.18%	11.79%
Min EF per part	9.06	6.38	8.05
Max EF per part	17.77	10.78	16.37

Integrating an alternative energy source significantly impacts the environmental footprint of the Rent & Move scenario with a 37% lower EF score per part than the Base Case. The Rent & Wait scenario also performs slightly better with solar panels than without. With Rent & Move, the benefits of changing to solar panels are immediate and can be leveraged on every part produced. In contrast, the Rent & Wait option only benefits from this change when the move occurs, though it is always more environmentally friendly than the Base Case scenario. As in the other analyses, the Rent & Move design sees a large disadvantage on the NPV side (240% lower NPV than the Base Case). The Rent & Wait model still exhibits a performance that lands between the other two for most of the metrics and dominates on the average (137% higher NPV than Base Case), standard deviation, and max NPV. The switch to a better energy provider does not match up to the impact of the renewable energy generation equipment when comparing the Base Case with the Rent & Move and Rent & Wait strategies.

Below in **Figure 76** and **Figure 77** is a graph regrouping the results for each investment and flexibility scenario investigated. For NPV and EF per part, the mean performance is shown in color, along with the min and max values as the dashed lines and the standard deviation displayed as error bars.

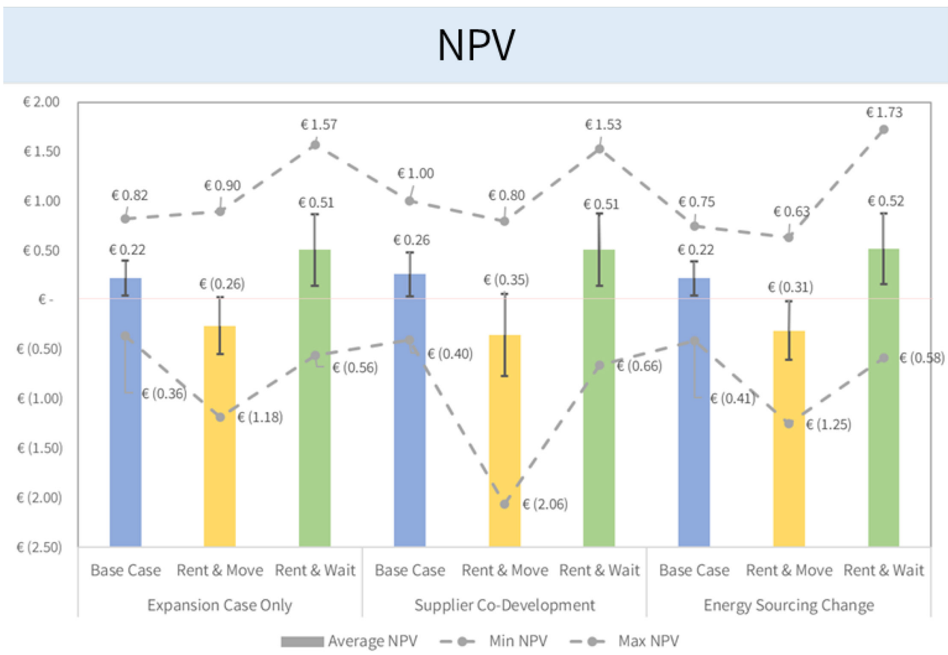

Figure 76. Statistical summary of flexibility analysis on NPV for all scenarios simulated.

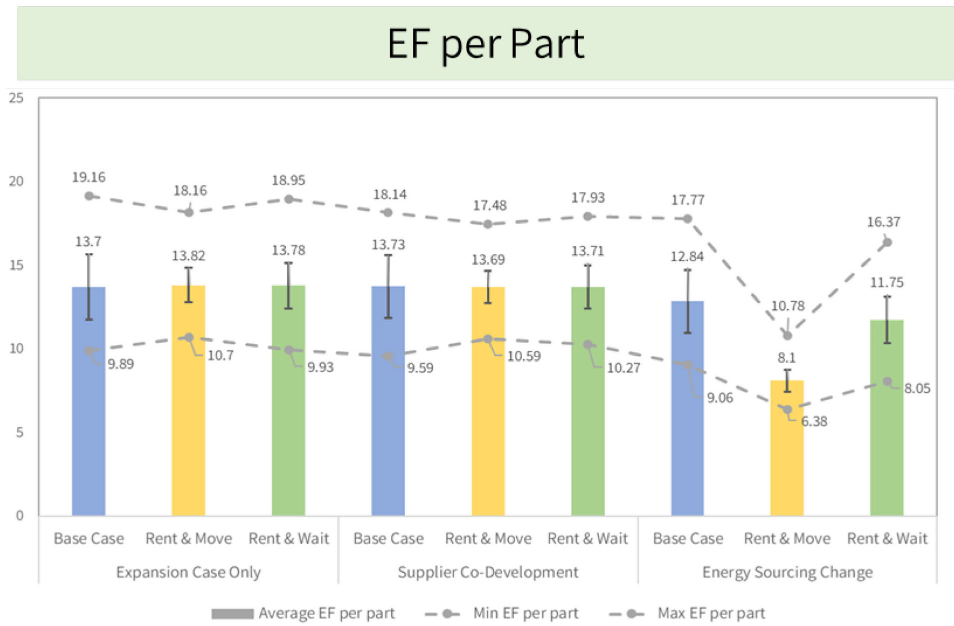

Figure 77. Statistical summary of flexibility analysis on EF score per part for all scenarios simulated.

5.5. Analysis Recommendations & Limitations

5.5.1. Selecting a Flexibility Strategy

Based on the observations described in this report and summarized in **Figure 76** and **Figure 77**, there is not a clear optimal strategy to recommend, but rather tradeoffs that will need to be further evaluated by the decision makers based on their tolerance for risk. The Base Case, simulating the current Add Lab strategy, has the advantage of limiting the negative financial performance compared to the two renting options by consistently exhibiting a higher minimum value. However, the current setup does not allow Add Lab to fully grow its profitability as demand grows leading to a low max NPV value. The Rent & Wait option exhibits the most promise in this dimension, although with a minimum NPV value that could be improved. Despite being the riskiest option from an NPV perspective, regarding the environmental footprint performance, the Rent & Move scenario appears to be the best solution, especially when considering the installation of renewable power generation equipment. In that regard, the Base Case is limited by its modification constraints and, therefore, generally performs the worst in EF score, especially when looking at the performance variability it yields. The Rent & Wait design is in between the Base Case and Rent & Move options. It is also important to note that the supplier incentives modeled did not improve the EF score per part for any of the scenarios, meaning that either reaching a "green premium" is required to see larger technological improvements or the projected rate of advancement is happening fast enough to capture as much environmental benefit with the current operations.

Based on this summary, and given the sustainability commitment of Decathlon, a blended strategy is recommended. The Add Lab should continue operating as is, with good control of its profitability, while looking for facilities to rent. Once the facility is identified and the property is ready, the team could move its two printers to the new facility (instead of 4 printers as simulated in the Rent & Move) and leverage the new energy sourcing options right away. Once the demand projections are clearer and the technological improvements' launch dates are more defined, additional printers can be purchased and installed without constraints since the space will be available. With this recommendation, it would also be interesting to better understand the availability of EU or government credits under acts such as the Green Deal Industrial Plan or the Net Zero Industrial Plan to support the move to a larger, more environmentally friendly facility. Identifying such support could make this transition more financially attractive. This new scenario could be modeled in this simulation to confirm its potential advantages before implementation.

5.5.2. Model Limitations

As an introductory analysis, this model contains numerous limitations.

1. Many averages were used to create this model. The average order size and the average part size are variables that deserve their own Monte Carlo simulation to model all the possible product volumes and sizes that could be ordered at Add Lab. Similarly, the inventory of environmental footprint inputs and outputs is based on averages of jobs varying in parts, materials, packing density, height, and durations. Since all averages need to be normalized to the functional unit of 1kg of printer part, there is an inherent flaw for values that do not scale with mass (e.g., printer energy consumption scales with build height rather than mass of printed material inside the build). The material properties were also averaged when, in reality, the material options are very distinct and discrete.

2. As hinted in point 1, these averages hid some of the non-linear relationships in the system. 3D printing is a batch process, meaning changes happen in "steps" rather than continuously.

3. Some variables were not accounted for in the performance equations. For example, in this model, the order size did not affect EF since the EF is based on a functional unit of kg of material manufactured. This is a faulty assumption since it would require more resources to execute 30 orders of 1 compared to 1 order of 30 parts. On the NPV side, the

process yield had no impact on the costs, which is also incorrect since if a part fails, one will have to print it again and, therefore, incur costs.

4. Some assumptions around the flexible options were also extremely simplified. The supplier incentive format incurred a one-time cost to improve release speed when, in a more realistic scenario, such an incentive would probably take longer and require more effort. An alternative incentive could come in the form of an upfront order payment from the customer to encourage progress by guaranteeing sales to the supplier. Regarding the facility rental, the time to move operations was set to 1 year, which may be feasible if the building is already owned by Decathlon, for example, but could be completely wrong if it is a new lease, and upgrades, permitting, and construction need to happen first. Finally, the expansion only involved the purchase of additional printers but ignored the need for more personnel and other equipment to support the higher demand and capacity, which could represent significant costs and should be included in further model iterations.

5. Lastly, in this analysis, no consideration for manufacturing and use location was embedded into the model. Treating the cost and EF single score of key parameters that depend on location as distributions could help consider the uncertainties tied to where the Add Lab will hold its operations and offer its services.

6. Case Study: Learnings & Future Work

6.1. Learnings from Applying Systems Modeling Methodologies to Add Lab's AM Service Strategy

By using tradespace analysis and flexible design analysis, all four strategic questions defined in the case study introduction were answered, balancing the need for financial and environmental sustainability. Even though specific objectives regarding the performance of Add Lab were not defined, the recommendations from these analyses have the potential to contribute to the company goals towards scope emissions reduction, product environmental footprint reduction, and circular economy enhancement.

On the one hand, the tradespace model helped inform the types of product and lifecycle decisions that maximize AM's environmental and economic value compared to injection molding, but also the ones that represent areas of improvement for the MJF technology to become more competitive with this conventional manufacturing method. Considering all the part types and lifecycle paths modeled and recognizing the limitation in the injection costing model, especially for low-volume production, the study determined that IM yields a unit cost, on average, 97% cheaper than AM, but AM yields, on average, 75% lower environmental footprint per part than IM. Small batches of small production parts, manufactured in Europe are the most ideal product and lifecycle decisions to increase the value of AM, meaning that large volumes of large parts in a mixed build configuration represent an area of development for MJF to compete with injection molding from a cost and environmental impact perspective.

On the other hand, the flexible design analysis guided the investment decisions Add Lab was facing regarding facility expansion, supplier incentives, and energy sourcing improvements. Moving to a new rental facility with more capacity and installing behind-the-meter power generation reduces the average environmental footprint per part by 37% compared to the current Add Lab setup, but renting and waiting for the demand to meet capacity before transferring operation and increasing footprint increases the NPV by 96-137% compared to the current base case scenario. For the assumptions used, the supplier incentives did not improve the profitability or environmental impact of Add Lab. Based on these conclusions, the recommendation is to adopt a hybrid plan where the current capacity should be transferred to a larger rental facility equipped with solar panels, and additional printers should be purchased when the demand for more capacity is there.

Beyond the recommendations, this study also helped uncover the advantages and limitations of each methodology. The tradespace was found to be very effective at simultaneously assessing the impact of many parameters on multiple performance metrics. Given the wide net this method casts, general trends could easily be observed, but the second-level drivers and interactions impacting performance were not always as clear. Data processing is needed to parse the information and pull out the explanations behind the tradespace graph. Flexible design analysis is a powerful tool to realistically assess investment and strategy design decisions. It encompasses many concepts between system modeling, decision rules, probabilities and uncertainties, and simulations. However, this level of tool integration comes at the price of complexity and generalization. Choices need to be made on the number of uncertainties considered to avoid overloading the model, and accessible platforms such as Excel can become a limitation if too much logic is modeled.

6.2. Implementation & Future Work Recommendations

This work serves as an introduction to the use of tradespace analysis and flexible design analysis for Add Lab's AM strategy planning and a foundation for further model development. Several suggestions for future work are gathered in this section to deepen this work in a holistic manner.

For both models, representatives of each function within the Add Lab team and adjacent teams should be involved and become active members in the improvement of this model. This integrated approach will enhance coordination, coherence, and value creation for the entire unit, leading to a more robust and performant strategy. In that same lens, the needs of the larger Decathlon organization, including its recent sustainability commitments, could be translated into specific targets, ensuring Add Lab's decisions have a clear and measurable impact on the broader company. Finally, having finalized and approved environmental impact measurements will tremendously help validate the value of these analysis tools and the findings they can generate.

For the tradespace model, several next steps are recommended:

1. The involvement of an injection molding expert would help resolve some of the calculation and assumption limitations encountered, especially around the mold.
2. Since the cradle-to-grave perspective is used, it would be important to also capture the impact of improved design, simplified supply chain, and enabled circular strategies on EF and cost when using additive manufacturing, and even consider a cradle-to-cradle scenario as suggested by Mecheter et al. [76].
3. The impact of after-sales repair parts should be better modeled via an "impact avoided" metric for cost and environmental footprint, or via more defined impact allocation rules, for example.
4. Uncertainty should be included in this analysis to provide a confidence level with the conclusions made from the static analysis. Along with this, different option parameter ranges, such as production volume, should be investigated.

For the flexible design analysis, here are suggestions for future developments:

1. The scenarios analyzed and the decisions and parameters values chosen for this model should be revised to ensure the most valuable insights can be extracted from this model. For example, considering metal additive manufacturing capabilities may be an area to assess prior to entertaining expansion options.
2. A cradle-to-grave approach could add additional insights regarding the impact associated with the supply chain and the various product service strategies Decathlon is promoting.
3. If considering the move to a new, larger facility, government and EU incentives should be investigated and factored into the model to better capture the financial attractiveness of the option.
4. As a strategy is selected, the functional representatives should remain engaged through the implementation phase. By having everyone involved, the knowledge of the flexible options and the parameters triggering the use of these options will be more easily maintained. An implementation plan should also be created and contain clear steps explaining when to exercise each flexible option. Beyond these implementation recommendations,

Both models could be used in tandem to inform each other, either on the future production capabilities that might dictate the types of products and lifecycle decisions that are more attractive to AM or on the production portfolio the Add Lab team should plan for in the demand projections when evaluating investment decisions. Finally, taking this from an even broader picture, the use of these modeling tools could reach beyond the Add Lab at Decathlon and start informing manufacturing and operations decisions across the company by integrating environmental sustainability as a key objective along with the traditional economic motive.

7. Conclusions

The overall purpose of this thesis work was to highlight the usefulness of quantitative system modeling and analysis methods to support decision-making at the company level for an AM service provider. The main contribution and novelty of this project lies in (1) the application of system modeling tools in the AM industry (2) to evaluate a large diversity of products a service unit at a consumer goods company manufactures, (3) considering environmental and financial metrics to define performance. This approach was demonstrated via a case study in the consumer goods industry with the Add Lab team at Decathlon. Using tradespace analysis, adapted from Crawley et al. [130], and flexible design analysis, developed by de Neufville and Scholtes [140], the environmental and economic aspects of AM were evaluated across a series of product, lifecycle, and investment decisions. Based on this case study, AM represents a promising technology to improve the environmental footprint of manufacturing but requires improvements to become more financially attractive compared to traditional manufacturing methods. Other quantitative but preliminary insights were gained, showing the potential of such tools for data-driven strategy planning.

As this study concluded, even if on the right track, the road to mainstream adoption of AM requires much more development work both from an application perspective and a technology and complementary asset point of view. Multiple implementation and deployment strategies have been suggested by market experts [13], [17] and scientific literature [54], and some even mention the need for a systems perspective to be used when approaching the adoption of AM [21]. However, given the complexity of the technology and the multitude of business models it can generate, there is a need to understand the value of AM and how to optimize for it before going into decision-making based on cost and environmental impact calculations [188]. This statement captures well the limitations of the models developed in this thesis work. Before we fully understand how to create, capture, and quantify the value of AM, like its free design optimization capability and its impact on the product lifespan, circularity, and overall value chain [6], [76], [189], it will be very challenging to validate and feel confident about any strategic decisions. However, both areas can be developed in parallel and grow to become versatile and comprehensive tools [48], integrating the latest developments in cost modeling and environmental sustainability assessment methods and the objectives of both internal and external stakeholders. Finally, there is a need to start accounting for the social impact of additive manufacturing, as existing research has been very focused on environmental and economic sustainability only [76], [190]. The inclusion of this third element would enable society to view the true, holistic opportunity additive manufacturing technologies represent.

Appendix A

Flexible Design Analysis – Static Base Model Case Analysis

DETERMINISTIC MODEL											
		2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
Year	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
TECHNOLOGY ADVANCEMENT PROJECTION											
3D Printer Manufacturer											
Process yield		93%	93%	93%	94%	94%	94%	94%	96%	96%	96%
Number of jobs per printer per day		1.5	1.5	1.5	2.0	2.0	2.0	2.0	3.0	3.0	3.0
Printer energy consumption		115	115	115	80	80	80	80	57	57	57
Printer cost											
3D Material Supplier											
Material loss per job		20%	15%	15%	15%	15%	10%	10%	10%	10%	10%
Material EF		700	490	490	490	490	350	350	350	350	350
Material cost											
DEMAND PROJECTION											
Demand Projection											
Prototype Parts		27000	27936	28483	28871	29173	29419	29627	29807	29966	30108
After Sales Repair Parts		3237	4856	8539	13668	19625	25792	31551	36284	39373	40200
Production Parts		176513	317509	458505	599501	740497	881493	1022489	1163485	1304481	1445477
Capacity Utilization		95%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Number of jobs per year		750	750	750	1000	1000	1000	1000	1500	1500	1500
Prototype		60%	62%	63%	48%	49%	49%	49%	33%	33%	33%
After Sales Repair Parts		7%	11%	19%	23%	33%	43%	51%	40%	44%	45%
Production Parts		28%	27%	18%	29%	19%	8%	0%	27%	23%	22%
After Sales Repair Parts produced in-house		3237	4856	8539	13668	19625	25792	30373	36284	39373	40200
Production parts produced in-house		176513	170506	111427	243872	156455	66887	0	333930	288566	275032
After-sales repair parts needing outsourcing		0	0	0	0	0	0	1178	0	0	0
Production parts needing outsourcing		0	147003	347078	355629	584042	814606	1022489	829555	1015915	1170445
COST											
CAPEX / Fixed Costs (non-recurring)	**€ -**										
Printer cost		€ -	€ -	€ -	€	€ -	€ -	€ -	€	€ -	€ -
Vacuum cost		€ -	€ -	€ -	€	€ -	€ -	€ -	€	€ -	€ -
Sandblasting machine cost		€ -	€ -	€ -	€	€ -	€ -	€ -	€	€ -	€ -
Dyeing machine cost		€ -	€ -	€ -	€	€ -	€ -	€ -	€	€ -	€ -
Vapor smoothing machine cost		€ -	€ -	€ -	€	€ -	€ -	€ -	€	€ -	€ -
Keyence machine cost		€ -	€ -	€ -	€	€ -	€ -	€ -	€	€ -	€ -
CAPEX / Fixed Costs (recurring)	**€ -**										
Facility cost											
CarePack cost											
Software cost											
PPE cost											
Labor cost											
OPEX / Variable Costs	**€ -**										
Material cost											
Agent cost											
Electricty cost											
Printer consumables cost											
Sandblasing media cost											
Water cost											
Dye cost											
Vapor smoothing consumable cost											
Finishing cost (only proto and repairs)											
Shipping cost											
Service Bureau Costs	**€ -**										
Total demand outsourced		0	147003	347078	355629	584042	814606	1023667	829555	1015915	1170445
Overhead cost											
REVENUE											
In-House											
Prototype parts unit cost											
Prototype parts revenue											
After sales repair parts unit cost											
After sales repair parts revenue											
Production parts unit cost											
Production parts revenue - regular											
Production parts revenue - urgent											
Production parts revenue - one-shot											
Service Bureau											
After sales repair unit cost											
After sales repair parts revenue - regular											
Service bureau unit cost											
Production parts revenue - regular											
Production parts revenue - urgent											
Production parts revenue - one-shot											
CASH FLOW											
Total Cash Flow	**€ -**	**€ 525,762.29**	**€ 563,629.33**	**€ 513,615.26**	**€ (1,865,721.54)**	**€ 513,224.11**	**€ 420,666.94**	**€ 350,962.08**	**€ (2,146,588.84)**	**€ 507,359.93**	**€ 511,306.19**
Discounted Cash Flow	**€ -**	**€ 477,965.72**	**€ 465,809.37**	**€ 385,886.74**	**€ (1,274,312.91)**	**€ 318,671.79**	**€ 237,455.52**	**€ 180,099.04**	**€ (1,001,399.54)**	**€ 215,170.14**	**€ 197,130.67**
ENVIRONMENTAL FOOTPRINT											
In-House EF per Part		**30.3**	**24.5**	**32.0**	**19.6**	**26.2**	**35.0**	**68.6**	**14.6**	**16.1**	**16.6**
Material EF (use + waste)		3074080	1642986	1569994	2284272	2183386	1233838	1188224	2061021	2030607	2020888
Agent EF (use only)		61272	63849	61012	88770	84850	80862	77872	135073	133079	132442
Sandblasting media EF (use + waste)		19980	20820	19895	29258	27965	26651	25666	45465	44795	44580
Electricty EF		2961476	3086036	2948935	2996001	2863681	2729083	2628191	3264256	3216086	3200692
Compressed air EF		153180	159623	152531	221926	212125	202154	194681	337682	332699	331106
Service Bureau EF per Part		**0.0**	**12.0**	**12.0**	**9.7**	**9.7**	**8.1**	**8.1**	**6.5**	**6.5**	**6.5**
Material EF (use + waste)		0	582522	1375349	1394242	2289734	1893755	2404417	1888331	2312545	2664305
Agent EF (use only)		0	22638	53448	54182	88983	124111	157578	123755	151557	174610
Sandblasting media EF (use + waste)		0	7382	17428	17858	29328	40905	51936	41656	51014	58774
Electricty EF		0	1094156	2583330	1828657	3003164	4188732	5318247	2990748	3662621	4219739
Compressed air EF		0	56594	133621	135456	222457	310276	393944	309388	378892	436525
Transportation EF		0	1103	2603	2667	4380	6110	7757	6222	7619	8778
Average EF per Part		**30.3**	**19.2**	**18.0**	**14.1**	**13.9**	**11.6**	**11.5**	**9.1**	**9.0**	**8.8**

Model Outputs	
NPV (in millions €)	**€ 0.20**
Average EF per Part	**14.6**

Figure 78. NPV and EF model of the static base case representing the evaluation of the current Add Lab model over the next 10 years.

Flexible Design Analysis – Base Case Analysis Model with Uncertainty

UNCERTAINTY MODEL											
Year	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
DEMAND PROJECTION											
Demand Projection		**179627**	**361590**	**585996**	**711812**	**631120**	**922470**	**904490**	**1484822**	**1482766**	**1517872**
Prototype parts demand projection		27000	27936	28483	28871	29173	29419	29627	29807	29966	30108
Deviation from forecast		8%	9%	8%	7%	1%	3%	4%	3%	2%	4%
Realized demand		28616	30227	30221	30272	26599	27975	29069	28842	28223	29690
Prototype average part size		31	41	37	29	29	33	33	41	37	28
After sales repair parts demand projection		3237	4856	8539	13668	19625	25792	31551	36284	39373	40200
Deviation from forecast		18%	14%	14%	1%	19%	5%	16%	25%	11%	3%
Realized demand		3561	4968	8834	10500	22354	21729	33600	45182	37887	32520
After sales repair average part size		51	47	48	58	52	45	51	48	59	41
Production parts demand projection		176513	317509	458505	599501	740497	881493	1022489	1163485	1304481	1445477
Deviation from forecast		4%	14%	22%	18%	2%	12%	4%	23%	17%	13%
Realized demand		147450	326395	546941	671040	582167	872766	841821	1410798	1416656	1455662
Production average part size		6	7	5	6	4	7	7	5	4	6
TECHNOLOGY ADVANCEMENT PROJECTION											
3D Printer Manufacturer											
Projection for new, more efficient printer model		NO	YES	NO	NO	NO	YES	NO	NO	NO	NO
Incentivize 3D printer manufacturer?	NO		NO								
Investment			€ -								
Process yield [%]		93%	93%	94%	94%	94%	96%	96%	96%	96%	96%
Number of jobs per printer per day		1.5	1.5	2	2	2	3	3	3	3	3
Printer energy consumption [kWh/job]		115	115	80	80	80	57	57	57	57	57
Printer cost											
Realized improvement?		NO	NO	YES	NO	NO	YES	NO	NO	NO	NO
3D Material Supplier											
Projection for more sustainable material		NO	YES	NO	NO	NO	YES	NO	NO	NO	NO
Incentivize 3D material supplier?	NO		NO								
Investment			€ -								
Material loss per job [%]		20%	20%	15%	15%	15%	10%	10%	10%	10%	10%
Material EF [dml/kg]		700	700	490	490	490	350	350	350	350	350
Material cost											
Realized improvement?		NO	NO	YES	NO	NO	YES	NO	NO	NO	NO
INFRASTRUCTURE DECISIONS											
Facility											
Invest in larger facility?	NO										
Is there a new, more efficient machine available?		NO	NO	YES	NO	NO	YES	NO	NO	NO	NO
How many printers is the future demand calling for?		3	3	3	3	4	3	4	4	4	N/A
Buy new printers and move to larger facility?	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Facility footprint [m2]		40	40	40	40	40	40	40	40	40	40
Facility lease cost [€/m2/yr]		€ 300.00	€ 300.00	€ 300.00	€ 300.00	€ 300.00	€ 300.00	€ 300.00	€ 300.00	€ 300.00	€ 300.00
Total number of printers	2	2	2	2	2	2	2	2	2	2	2
Original printers - process yield	93%	93%	93%	93%	94%	94%	94%	94%	96%	96%	96%
Original printers - energy consumption	115	115	115	115	80	80	80	80	57	57	57
Original printers - number of jobs per printer per day	1.5	1.5	1.5	1.5	2	2	2	2	3	3	3
Original printers - cost											
New printers - process yield	93%	93%	93%	94%	94%	94%	96%	96%	96%	96%	96%
New printers - energy consumption	115	115	115	80	80	80	57	57	57	57	57
New printers - number of jobs per printer per day	1.5	1.5	1.5	2	2	2	3	3	3	3	3
New printers - cost											
Average process yield		93.0%	93.0%	93.0%	94.0%	94.0%	94.0%	94.0%	96.0%	96.0%	96.0%
Average energy consumption		115	115	115	80	80	80	80	57	57	57
Average number of jobs per printer per day		1.5	1.5	1.5	2	2	2	2	3	3	3
Average annual job capacity		750	750	750	1000	1000	1000	1000	1500	1500	1500
Average printer cost (for revenue calc)											
Energy Source											
Invest in cleaner energy source?	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Investment cost [€]	€ -										
Electricity cost [€/kWh]		€ 0.10	€ 0.10	€ 0.10	€ 0.10	€ 0.10	€ 0.10	€ 0.10	€ 0.10	€ 0.10	€ 0.10
Electricity EF [dml/kWh]		25	25	25	25	25	25	25	25	25	25
Capacity Utilization		**95%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Prototype		64%	67%	67%	50%	44%	47%	48%	32%	31%	33%
After Sales Repair Parts		8%	11%	20%	18%	37%	36%	52%	50%	42%	36%
Production Parts		23%	22%	13%	32%	18%	17%	0%	18%	27%	31%
After sales repair parts produced in house		3561	4968	8834	10500	22354	21729	30931	45182	37887	32520
Production parts produced in-house		147450	136944	83032	268552	154290	143801	0	223132	333664	388134
After sales repair parts needing outsourcing		0	0	0	0	0	0	2669	0	0	0
Production parts needing outsourcing		0	189451	463909	402488	427877	728965	841821	1187666	1082992	1067528
COST											
CAPEX / Fixed Costs (non-recurring)	**€ -**										
Printer cost	€ -	€ -	€ -	€ -	€	€ -	€ -	€ -	€	€ -	€ -
Vacuum cost		€ -	€ -	€ -	€	€ -	€ -	€ -	€	€ -	€ -
Sandblasting machine cost		€ -	€ -	€ -	€	€ -	€ -	€ -	€	€ -	€ -
Dyeing machine cost		€ -	€ -	€ -	€	€ -	€ -	€ -	€	€ -	€ -
Vapor smoothing machine cost		€ -	€ -	€ -	€	€ -	€ -	€ -	€	€ -	€ -
Keyence machine cost		€ -	€ -	€ -	€	€ -	€ -	€ -	€	€ -	€ -
3D printer development incentive	€ -	€ -	€ -	€ -	€	€ -	€ -	€ -	€	€ -	€ -
3D material development incentive	€ -	€ -	€ -	€ -	€	€ -	€ -	€ -	€	€ -	€ -
Renewable installation	€ -										
CAPEX / Fixed Costs (recurring)	**€ -**										
Facility cost											
CarePack cost											
Software cost											
PPE cost											
Labor cost											
OPEX / Variable Costs	**€ -**										
Material cost											
Agent cost											
Electricty cost											
Printer consumables cost											
Sandblasing media cost											
Water cost											
Dye cost											
Vapor smoothing consumable cost											
Finishing cost (only proto and repairs)											
Shipping cost											
Service Bureau Costs	**€ -**										
Total demand outsourced		0	189451	463909	402488	427877	728965	844490	1187666	1082992	1067528
Overhead cost											

Continued on next page

REVENUE											
In-House											
Prototype parts unit cost											
Prototype parts revenue											
After sales repair parts unit cost											
After sales repair parts revenue											
Production parts unit cost											
Production parts revenue - regular											
Production parts revenue - urgent											
Production parts revenue - one-shot											
Service Bureau											
After sales repair unit cost											
After sales repair parts revenue - regular											
Service bureau production unit cost											
Production parts revenue - regular											
Production parts revenue - urgent											
Production parts revenue - one-shot											
CASH FLOW											
Total Cash Flow	**€ -**	**€ 456,070.10**	**€ 642,821.74**	**€ 557,024.76**	**€ (1,855,478.12)**	**€ 395,713.36**	**€ 456,670.24**	**€ 208,188.65**	**€ (2,206,052.03)**	**€ 640,917.90**	**€ 524,890.09**
Discounted Cash Flow	**€ -**	**€ 414,609.18**	**€ 531,257.64**	**€ 418,500.95**	**€ (1,267,316.52)**	**€ 245,706.87**	**€ 257,778.45**	**€ 106,833.69**	**€ (1,029,139.55)**	**€ 271,811.76**	**€ 202,367.85**
ENVIRONMENTAL FOOTPRINT											
In-House EF per Part		**34.3**	**44.5**	**31.3**	**19.3**	**24.2**	**19.8**	**55.7**	**19.4**	**14.9**	**12.9**
Material EF (use + waste)		3018440	3757061	1551274	2429295	2000189	1351883	1179466	2033625	2100695	2045701
Agent EF (use only)		60163	74885	60285	94406	77730	88598	77298	133277	137673	134069
Sandblasting media EF (use + waste)		19618	24419	19658	31115	25619	29201	25477	44861	46341	45127
Electricty EF		2907874	3619439	2034617	3186210	2623403	2141118	1868044	3220865	3327092	3239992
Compressed air EF		150407	187212	150712	236016	194326	221495	193246	333193	344182	335172
Service Bureau EF per Part		**0.0**	**18.9**	**11.6**	**11.6**	**11.6**	**7.8**	**7.9**	**7.8**	**7.8**	**7.8**
Material EF (use + waste)		0	1756459	2182503	1893542	2012987	1991227	2361472	3244206	2958281	2916039
Agent EF (use only)		0	35009	84816	73586	78228	130499	154763	212615	193876	191108
Sandblasting media EF (use + waste)		0	11416	27954	24253	25783	43926	52093	71566	65259	64327
Electricty EF		0	1692119	2862523	2483529	2640190	3153715	3740112	5138190	4685340	4618438
Compressed air EF		0	87523	212039	183965	195570	326246	386908	531537	484690	477769
Transportation EF		0	1705	4175	3622	3851	6561	7781	10689	9747	9608
Average EF per Part		**34.3**	**31.1**	**15.7**	**14.9**	**15.7**	**10.3**	**11.1**	**10.1**	**9.7**	**9.3**
Model Outputs											
NPV (in millions €)	**€ 0.15**										
Average EF per Part	**16.2**										

Figure 79. *Model of the base case NPV and EF analysis representing one simulation including uncertainty.*

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