Titre: Title:	A Stochastic Eco-Efficiency Approach to Support the Eco-Design of Additive Manufactured Components in the Aircraft Industry
Auteur: Author:	Elsa Moawad
Date:	2019
Type:	Mémoire ou thèse / Dissertation or Thesis
Référence: Citation:	Moawad, E. (2019). A Stochastic Eco-Efficiency Approach to Support the Eco-Design of Additive Manufactured Components in the Aircraft Industry [Master's thesis, Polytechnique Montréal]. PolyPublie. https://publications.polymtl.ca/3839/

URL de PolyPublie: PolyPublie URL:	https://publications.polymtl.ca/3839/
Directeurs de recherche: Advisors:	Manuele Margni, Vladimir Brailovski, & Thomas Dandres
Programme: Program:	Maîtrise recherche en génie industriel

POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

A Stochastic Eco-Efficiency Approach to Support the Eco-Design of Additive Manufactured Components in the Aircraft Industry

ELSA MOAWAD

Département de mathématiques et de génie industriel

Mémoire présenté en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

Génie industriel

Avril 2019

POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

Ce mémoire intitulé :

A Stochastic Eco-Efficiency Approach to Support the Eco-Design of Additive Manufactured Components in the Aircraft Industry

présenté par **Elsa MOAWAD**

en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

a été dûment accepté par le jury d'examen constitué de :

Réjean SAMSON, président

Manuele MARGNI, membre et directeur de recherche

Thomas DANDRES, membre et codirecteur de recherche

Vladimir BRAILOVSKI, membre et codirecteur de recherche

Annie LEVASSEUR, membre

DEDICATION

To my parents, for giving themselves to offer me an education and a life worth living.

To my dad, for always reminding me to make the best use of my time.
"Every second is of infinite value".
Johann Wolfgang von Goethe

To my mum, for knowing when to hold me close and when to let me go.
“Vos enfants ne sont pas vos enfants. Ils sont les fils et les filles de l’appel de la Vie à la Vie”.
Gibran Khalil Gibran

To work.
“Et je vous dis que la vie est en effet obscure sauf là où il y a élan,
Et tout élan est aveugle sauf là où il y a la connaissance.
Et toute connaissance est vaine sauf là où il y a le travail,
Et tout travail est futile sauf là où il y a l’amour;”
Gibran Khalil Gibran

To perseverance.
“It does not matter how slowly you go as long as you do not stop”.
Confucius

To happiness.
“Happiness only real when shared”.
Christopher McCandless

ACKNOWLEDGEMENTS

Being part of the CIRAIG and pursuing my master's degree had been a dream for me when I was back in Lebanon. Here I am today, a step away from making it come true. I would like to thank each person that has been part of this journey and has helped me make it through the end.

I would like to thank Manuele, Thomas and Vladimir for agreeing to supervise me. Thank you for supporting me all the way. I am grateful for your patience, your time, and everything you have done to help me complete my thesis. Thank you Manuele for your guidance and wisdom, and for not letting me down at the hardest times. You have helped me improve on a professional but also personal level. Thank you for your humbleness, your professionalism but also the great person you are. Thank you Thomas for replying to the first email I had sent to the CIRAIG, without you I maybe wouldn't be here today. Thank you for being here to answer every question I had, for listening to me and encouraging me to go further. Finally, thank you Vladimir for sharing with me your passion for additive manufacturing, for showing me how much one can give when they love what they do, and thank you for kindly welcoming me into your research group and offering me everything I needed in order to succeed.

A big thank you to the people with whom I have collaborated. Thank you Pascal for sharing your knowledge on uncertainty and for every meeting or conversation we have had which brought me a step closer to my goal. Thank you Laure for the times where you have helped me understand things I never thought I would understand. Thank you Catherine for our enlightening and challenging discussions. Thank you Ali and Philippe for your help regarding the case study. Thank you Anatolie, Morgan, Victor and Olivier for assisting me on the additive manufacturing aspect of my research.

I would also like to acknowledge the CIRAIG and industrial partners of the Manu-710 project who have supported me financially and given me the opportunity to pursue my graduate studies.

Thank you to the CIRAIG family for showing me the best work environment one could ever have. Thank you to the analysts for their professional support. Thank you Sophie, Sara and Anne-Marie for your beautiful personalities and inspiring leadership. Thank you Laurence for your kindness and caring. Thank you to my student colleagues for sharing beautiful, crazy but also serious moments. Thank you to those who became my friends and family.

To my friends in Canada, Lebanon and around the world, thank you for being here for me and encouraging me. Thank you to Lea H. and Alain for their never-ending support. Finally, thank you to my family, to Mum, Pap, Sarah and Lea, for believing in me and for giving me the strength to persevere throughout this journey.

RÉSUMÉ

Lorsque l'on est confronté à des indicateurs de coûts et d'impacts environnementaux, prendre des décisions s'avère assez difficile, surtout lorsque l'atténuation des impacts se fait au détriment d'un coût additionnel. Malgré cela, notre monde fait face à une augmentation des gaz à effet de serre et par la suite, un changement pragmatique dans notre manière de penser et de concevoir nos systèmes est primordial. L'industrie aéronautique est responsable d'environ 2% des émissions mondiales de gaz à effet de serre et a reconnu la nécessité d'adopter une vision cycle de vie afin de réduire ses impacts sur l'environnement. Dans ce contexte-là, les partenaires industriels de ce projet ont misé leur attention sur le potentiel de l'écoconception de pièces d'avions produites par fabrication additive. Par conséquent, l'objectif général de cette recherche est d'intégrer l'analyse d'incertitude à une approche d'écoconception basée sur le concept d'éco-efficience, afin de soutenir et d'éclairer la prise de décision. La méthodologie est développée autour d'une étude de cas sur la fabrication additive de pièces d'avions comparée à une technique de fabrication conventionnelle, l'usinage.

Une analyse du cycle de vie (ACV) de type distance par rapport à l'objectif par facteur de réduction est utilisée pour calculer les impacts environnementaux potentiels en termes d'émissions de dioxyde de carbone, oxydes d'azote et particules fines. Ces émissions font l'objet de l'attention du secteur aéronautique qui s'est fixé des objectifs de réduction sur des horizons de temps bien définis. L'analyse environnementale des coûts du cycle de vie est utilisée pour calculer les coûts générés tout au long du cycle de vie de l'avion en les actualisant à l'année de référence (2018).

Les résultats de l'ACV et des coûts du cycle de vie sont intégrés dans un diagramme d'éco-efficience afin d'identifier et de choisir les alternatives de conception les plus éco-efficientes. Étant donné qu'une décision implique toujours un certain niveau de risque, nous intégrons à cette approche une évaluation quantitative de l'incertitude basée sur une méthode probabiliste afin d'estimer le niveau de confiance donné aux résultats. Ces-derniers sont comparés en évaluant la différence statistique significative qui existe entre les scores d'ACV, de coûts et d'éco-efficience des alternatives de conception. Finalement, une analyse de sensibilité globale est réalisée afin d'identifier les paramètres d'entrée du modèle qui contribuent le plus à l'incertitude des résultats.

L'étude de cas montre, à travers les résultats, que la fabrication additive est une technologie prometteuse pour le secteur de l'aéronautique puisqu'elle permet à la fois une amélioration environnementale et une réduction des coûts donc une meilleure éco-efficience comparée à

l’usinage. Ces avantages sont principalement dus à l'optimisation topologique; en effet, la probabilité que cette pièce soit plus éco-efficiente que celle fabriquée de manière conventionnelle est significative. L'analyse de sensibilité globale montre que la variabilité de paramètres tels que la distance parcourue par l'avion tout au long de sa durée de vie, la consommation de carburant, le coût de production et le taux d'actualisation, contribue le plus à l’incertitude des résultats. Par conséquent, raffiner ces paramètres contribuerait à faciliter la prise de décision. L'ACV de type distance par rapport à l’objectif par facteur de réduction est pertinente pour l'industrie aéronautique, car elle soutient l'atteinte des objectifs de réduction fixés. Néanmoins, les résultats ne tiennent pas compte du profil environnemental global car la méthode est limitée aux émissions de certaines substances uniquement. Afin de veiller à la bonne opérationnalisation de l’écoconception pour la fabrication additive, la prise en compte de l’ensemble des émissions orienterait des choix plus durables.

Enfin, il faudrait saisir l'écoconception comme une opportunité de guider des choix plus éco-efficients, tôt dans le processus de développement de produits. La fabrication additive est une technologie en pleine évolution. Par suite, il faudrait s’assurer d’intégrer l’écoconception de façon cohérente et adaptée, afin de s’assurer que les choix, côté technique, génèrent le moins d’impacts possible tout en restant rentables. L'incertitude peut être minimisée tout au long du processus et le temps de calcul pour son évaluation est court. Cependant, les résultats de l’analyse sont liés aux choix des distributions des paramètres d’entrée. Le travail préliminaire de définition de ces distributions dépend de notre connaissance de la variabilité des paramètres. La collecte de telles données pourrait en effet limiter les efforts pour mettre en œuvre une telle approche.

ABSTRACT

When confronted with cost and environmental indicators, making a decision is very often complicated. This is mostly true when improving the environment is at the expense of an additional cost. Nevertheless, with a world experiencing an increase of greenhouse gas (GHG) emissions, a shift in the way we operate our processes and design our systems is needed. The aircraft industry emits about 2% of the world GHG emissions and has acknowledged the need for a life-cycle perspective in order to reduce its environmental impacts, eventually ensuring a safer environment and cleaner air quality for humans. In this context, the industrial partners of this project have drawn their attention to the potential of eco-design in additively manufactured aircraft parts. Consequently, the general objective of this project is to integrate uncertainty knowledge into an eco-design approach built on the eco-efficiency (EE) concept, in order to support informed and robust decisions from a life-cycle perspective. The methodology is developed around a case study on Additive Manufacturing (AM) of aircraft parts compared to Conventional Manufacturing (CM).

A distance-to-target Life-Cycle Assessment (LCA) is used to calculate the potential environmental impacts in terms of Carbon dioxide (CO_2), Nitrogen Oxides (NO_x) and Particulate Matter (PM) emissions. In fact, these are the emissions of interest for which the aeronautical industry has set reduction targets. In parallel to the LCA, the environmental Life-Cycle Costing (LCC) is used to calculate cash flows occurring throughout the aircraft lifetime by discounting them to the reference year (2018). LCA and LCC results are combined into an eco-efficiency diagram in order to identify and choose the most eco-efficient design alternative. Because making decisions always implies a given level of risk, a stochastic uncertainty assessment is integrated into the eco-design approach in order to evaluate the confidence given to results. The scenarios are compared under uncertainty by calculating the probability of a scenario being better than another in terms of LCA, LCC and EE scores. Finally, a global sensitivity analysis is performed in order to identify the input parameters contributing the most to the results uncertainty.

The case study results show that AM is a promising technology for the aircraft sector in terms of the environmental, economic and eco-efficiency improvements it enables. These benefits are mostly achievable through topology optimization; the probability of such part being more eco-efficient than the conventionally manufactured one is found to be significant. The global sensitivity analysis shows that the variability of parameters such as the distance travelled by the aircraft

throughout its lifetime, the fuel consumption, the production cost and the discount rate contribute the most to the results uncertainty. Therefore, refining these parameters would help increase the ease of decision-making.

The distance-to-target LCA is a relevant approach for the aeronautical industry because it helps achieve the reduction targets set for the emissions of interest. However, the results do not account for global emissions. In order to successfully integrate eco-design for AM, accounting for the complete environmental profile of parts would guide potential improvements towards areas of protection such as ecosystems quality.

Finally, implementing eco-design is a good opportunity to guide eco-efficient choices as the technology evolves, yet still needs to be integrated consistently with “Design for Additive Manufacturing” to ensure each technical choice generates the lowest possible impacts while remaining cost-efficient. Uncertainty can be minimized throughout the process and can be evaluated in a short computation time. However, the assessment results are related to the input parameters distributions used; the preliminary work of defining these distributions depends on our knowledge about input parameters variability. Thus, data collection could limit the efforts to implementing such an approach.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

3D	Three Dimensional
AAMI	Aerospace Additive Manufacturing Initiative
AM	Additive Manufacturing
ASTM	American Society for Testing and Materials
CAD	Computer Aided Design
CAM	Computer Aided Manufacturing
CARIC	Consortium for Aerospace Research and Innovation in Canada
CIRAIG	International Reference Centre for the life-cycle of products, processes and services
CO_2	Carbon Dioxide
CRIAQ	Consortium de Recherche et d'Innovation en Aérospatiale du Québec
DALY	Disability Adjusted Life Year
EE	Eco-efficiency
EOL	End-of-life
ETS	Ecole de Technologie Supérieure
GHG	Greenhouse Gas
GLO	Global
GPS	Guided product search
GSA	Global sensitivity analysis
HIP	Hot isostatic pressing
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
ISO	International Organization for Standardization
LAMSI	Laboratoire sur les Alliages à mémoire et Systèmes Intelligents

LCA	Life-Cycle Assessment
LCC	Life-Cycle Costing
LCI	Life-Cycle Inventory
LCIA	Life-Cycle Impact Assessment
LPBF-AM	Laser Powder Bed Fusion Additive Manufacturing
MJ	Mega Joules
NO_x	Nitrogen Oxides
PM	Particulate matter
PDF	Potentially Disappeared Fraction
R&D	Research and Development
RER	Europe
RoW	Rest of the World
RP	Rapid Prototyping
SLCA	Social Life-Cycle Assessment
SO_x	Sulfur oxides
STL	Stereolithography
Yr	Year

LIST OF APPENDICES

CHAPTER 1 INTRODUCTION

The world has experienced an increase of about 60% of CO_2 emissions between 1990 and 2013 (Oak Ridge National Laboratory [ORNL], 2017). The aviation sector alone emits 2% of the greenhouse gas (GHG) emissions (European Commission, 2015) and is the second largest fuel consumer worldwide (International Energy Agency [IEA], 2010). This sector has been showing a willingness to reduce its environmental impact by adopting new strategies for sustainability. As described in the International Air Transport Association Technology Roadmap (IATA, 2013), the emissions of main concern for this sector are carbon dioxide (CO_2), nitrogen oxides (NO_x) and particulate matter (PM). In fact, the roadmap has set a 50% CO_2 reduction target by 2020 and 75% by 2050; 80% NO_x reduction by 2020 and 90% by 2050 and 65% PM reduction by 2050. Furthermore, the International Civil Aviation Organization Council (ICAO, 2017) elaborated a standard for aircraft designs in order to reduce the environmental impact of the aviation industry in terms of CO_2 emissions. The aircrafts "in-production which by 2028 do not meet the standard will no longer be able to be produced unless their designs are sufficiently modified" (ICAO, 2017).

Additive manufacturing (AM) arises as one of the opportunities to reaching these ambitious targets. This technology has experienced a growing interest from manufacturers since the beginning of the twenty first century, because of its potential for functional integration[1] (Attaran, 2017; Tang, Mak, & Zhao, 2016). It also broadens design opportunities through innovation, increasing its competitiveness compared to Conventional Manufacturing (CM) (Wohlers, 2014).

In fact, many studies have shown that AM could address sustainability challenges when compared to CM. For example, AM has the ability to produce lightweight components, therefore saves fuel during the use phase and potentially lowers the carbon footprint over the entire life-cycle. Actually, it has been shown that over 90% of an aircraft potential environmental impacts originate from its use phase (CIRAIG, 2018). Mitigating these impacts can be done by adopting a life-cycle perspective. In fact, aircraft components are designed early in the product and development phase. Rethinking their design and their production can help anticipate their damage to the environment, and can be achieved through eco-design. It is an approach aiming to guide the product development

---

[1] functions achieved by multiple components can be merged and achieved by one component

process and support the design of environmental-friendly products (Bhander, Hauschild, & McAloone, 2003). As a matter of fact, it derives from sustainable development. The latter sets the focus on stimulating change in manufacturing, technological and social organization management, in order to create economic growth where humans are able to meet their "present needs without compromising the ability of future generations to meet theirs" (Wrisberg, Haes, Triebswetter, & Eder, 2002). Therefore, it implies making difficult choices and requires that the industrial activity be reconfigured.

This research is realized as part of the Aerospace Additive Manufacturing Initiative (AAMI) lead by the Consortium for Aerospace Research and Innovation in Canada (CARIC). Two leaders of the aeronautical industry, Bell Helicopter Textron Canada Limited and Pratt & Whitney Canada, have carried out projects on AM processes and faced similar challenges, translating their mutual interest for collaboration. The purpose of this project, Manu-710, is to bring together most actors of the AM value chain in order to participate in the progress of this technology, compared to CM. The collaboration aims to better understand how a part produced by AM can meet technical requirements. Some expected benefits from this project are "CO_2 emissions reduction via weight reduction and cost reduction through part assembly integration, lead time reduction, reduced buy-to-fly ratio, reduced inventory and optimized batch size" (CIRAIG, 2018).

The project is developed around a case study on the design of an aircraft engine component by conventional and additive manufacturing technologies. The aim is to compare them, assess their environmental and economic performances and identify improvement paths for research and development.

In this context, the importance of an eco-design approach to integrate environmental aspects early in the design stages is acknowledged. This is possible through decision-making support tools, such as the Life-Cycle Assessment (LCA). It allows one to quantify the potential environmental impacts of products, processes or services throughout their complete life-cycle, i.e. from raw material extraction to their end-of-life (International Organization for Standardization [ISO], 2006a, 2006b). LCA enables the identification of "hot spots" and impact displacement, making it one of the most powerful eco-design tools.

Nevertheless, alone, LCA is not enough to influence the choice of scenario because the costs are predominant. The concept of eco-efficiency is key in order to combine the environmental and economic dimensions.

Moreover, uncertainty is prevalent in life-cycle impacts and costs (Gregory, Noshadravan, Swei, Xu, & Kirchain, 2017). It is inherent to long lifetimes (such as that of an aircraft) and the evolutions of both the economic and environmental data over time. This underlying uncertainty limits the conclusions of such assessments. It needs to be evaluated systematically in order to provide confidence and robustness to the results and therefore, support decisions.

Consequently, the general objective of this project is to integrate uncertainty knowledge into an eco-design approach built on the eco-efficiency concept in order to help industrial partners make informed and robust decisions from a life-cycle perspective. This approach is built around a case study on additive manufacturing applied to the aeronautical industry.

CHAPTER 2 LITERATURE REVIEW

2.1 Additive Manufacturing

This section describes AM, its environmental and cost challenges along with its limitations for the aeronautical industry.

2.1.1 Definition and process overview

Additive Manufacturing was initially called “Rapid Prototyping” (RP). It was used to define processes which resulted in prototypes, from which other models were derived. Afterwards, the term “additive manufacturing” appeared to group all technologies “using the additive approach”: a Three Dimensional Computer Aided Design (3D CAD) system is used to generate a 3D model that is further fabricated by adding material layer by layer (Gibson, Rosen, & Stucker, 2010; International Organization for Standardization [ISO/ASTM], 2015).

Most of these processes include eight steps represented in Figure 2.1 (adapted from Gibson et al. (2010)). First, the three-dimensional solid is constructed on a CAD system. It is then converted to the stereolithography (STL) format, which is the standard for almost all AM machines. Afterwards, the file is transferred to the machine and manipulated in order to setup the component size, orientation and position. Next, the machine is setup, meaning all parameters required for the building are configured. The printing can take place without any major supervision and only needs to be checked on from time to time in case any error occurs. Once done, the component is separated from the build plate (also called platform) and cleaned. If any support structure was added, it is removed (the plate separation and support removal steps are sometimes done after post-processing). The post-processing steps aim to adjust mechanical properties and reduce internal stresses resulting from the printing (because of voids or bubbles trapped inside the part, links between layers may not be bonded in an optimum way).

These steps are achieved by processes such as stress relief heat treatment and hot isostatic pressing (HIP). Additionally, post-AM activities (drilling, milling, i.e. conventional techniques) can be done to subtract additional material thickness (called machining allowance). Finally, the component goes through surface finishing and painting if needed, before the parts are ready to be used (Gibson et al., 2010). All these activities should ensure that in the end, surface quality meets the product requirements (Brandt, 2016).

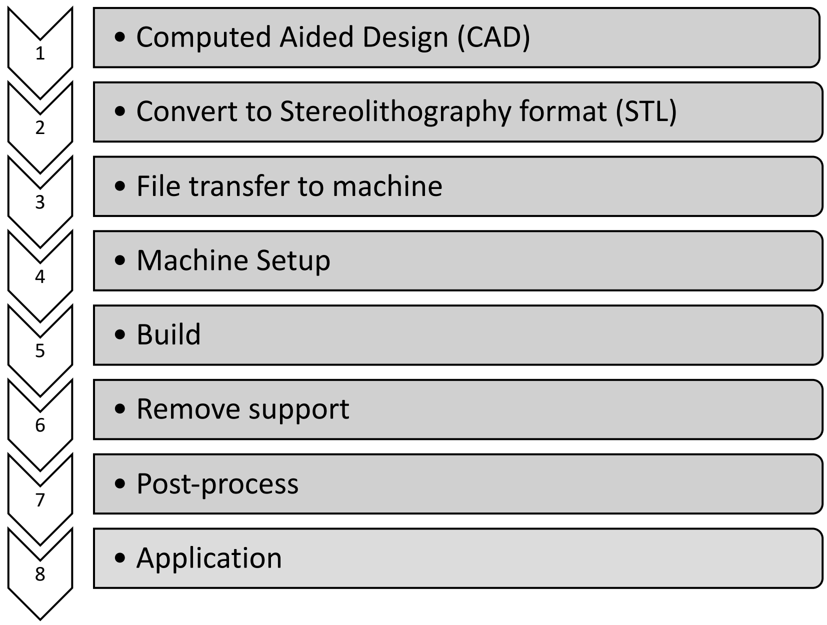


Figure 2.1: Generic process of additive manufacturing (adapted from Gibson et al. (2010))

The three main inputs of the AM process are material (metallic, non-metallic or composite materials), energy (laser, light or electron beam) and the CAD model. The amount of energy to use depends on the beam type (e.g. laser or electron beam), the power of the beam source, the material, the cooling unit and the layer thickness (Burkhart & Aurich, 2015).

2.1.2 Topology Optimization

Topology optimization (Figure 2.2) rethinks the material distribution within a given space, for a given set of loading and boundary conditions, in order to find an optimal load path for the particular loading and boundary conditions. It is the most general structural optimization technique enabling a weight reduction and is mainly considered at a conceptual design stage of AM (Bendsøe & Sigmund, 2004).

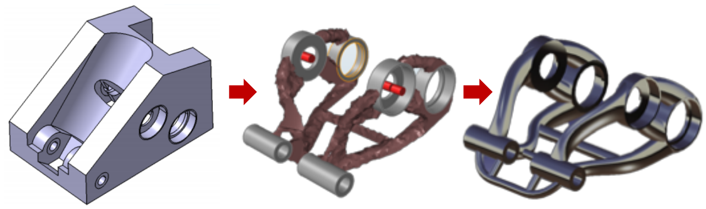


Figure 2.2: Topology optimization carried out on a component at the Laboratoire sur les alliages à mémoire et systèmes intelligents (LAMSI)

2.1.3 Additive manufacturing technologies

Additive manufacturing technologies differ depending on the materials used, the layers production and the bonds between them. These parameters lead to differences in the accuracy of the final part, its mechanical properties, the time needed for its production, the need for post-processing, the size of the machine, and the overall cost of the machine and process (Gibson et al., 2010). The environmental impacts and costs are expected to vary according to the technology and material selected.

Although the terminology for the different technologies has very often been debated (Mota, Puppi, Chiellini, & Chiellini, 2015), the ISO/ASTM (2015) standard breaks them down into 7 groups: *material extrusion* (material is selectively distributed through a nozzle), *material jetting* (droplets of material are deposited), *powder bed fusion* (the powder bed is fused by region with thermal energy), *direct energy deposition* (materials are fused by thermal energy as they are being deposited), *photo polymerization* (the liquid photopolymer undergoes light-activated polymerization), *sheet lamination* (sheets of material are bonded), and finally *binder jetting* (powder materials are joint by a liquid bonding agent) (ISO/ASTM, 2015; Réseau-Québec-3D, 2016). In this project, only powder bed fusion is addressed.

2.1.4 Additive manufacturing versus conventional manufacturing

AM distinguishes itself from conventional techniques by the reduced amount of material needed for the product (Morrow, Qi, Kim, Mazumder, & Skerlos, 2007). While conventional manufacturing includes a wide set of processes, the ones addressed here are subtractive methods such as milling, cutting, turning. In other words, the term "conventional manufacturing" or "machining" will be used to define the process of removing material from a bounding volume using subtractive tools. Table 2.1 below provides a technical comparison summary between both types of technologies (Gibson et al., 2010).

Table 2.1: Comparison between AM and CM (summarised from Gibson et al., (2010))

	Additive Manufacturing	**Conventional Manufacturing**
Material	· Polymeric material, waxes, paper laminates, composites, metals, ceramics · Voids, anisotropy, unpredictable quality	· Soft materials, foams, waxes, polymers, steel, metal alloys · Homogeneous, predictable quality
Production volume	· Single part production possible · Batch production limited to the surface of the build platform	· Single production discouraged · Batch production adequate
Geometry Complexity	· Very adequate for complex and customized geometries · No need for additional tooling	· Not compatible with very complex components · Additional tooling required
Accuracy	· Resolution varies in all directions · Function of the properties of the build material	· Resolution varies in the 3 directions · Function of the properties of the build material
Programming	· Less complex program sequence than CM · Incorrect programming only leads to imperfect parts	· Very complex program sequence (speed, tool selection, approach position, angle, etc.) · Incorrect programming damages the machine, endangers user, and leads to imperfect components

It is clear that these two types of technologies rely on multiple parameters affecting their overall technical and, with no doubt, economic and environmental performances.

2.1.5 Potential of additive manufacturing for the aeronautical industry

Sustainability of additive manufacturing along with the advantages and challenges of its adoption have been reviewed exhaustively by many authors (Malshe, Nagarajan, Pan, & Haapala, 2015). However, only three main trends of interest in this project are highlighted below.

On one hand, the greatest potential and trend of AM for the aeronautical industry is due to the high demand for lightweight structures, interior customization and fuel reduction (Pinkerton, 2016). In fact, topology optimization is the major benefit offered by AM which leads to weight reduction of parts (Huang et al., 2016) and therefore a decrease in the amount of fuel consumed (9-33% reduction) during the use phase of an aircraft (Gebler, Uiterkamp, & Visser, 2014). Approximately 1.2 to 2.8 billion GJ of primary energy and 92 to 215 million metric tons of greenhouse gas emissions are estimated to potentially be saved in the United States by 2050 using AM for lightweight metallic aircraft parts instead of the conventional methods (Huang et al., 2016).

On another hand, the use of additive manufacturing as a rapid production technology has increased significantly (Pinkerton, 2016) mostly for its material and tool efficiency (Huang et al., 2016): thousands of tons of aluminum, titanium and nickel alloys could potentially be saved per year by 2050 (Huang et al., 2016). This is because additive manufacturing helps decreasing metal losses during the production process. Although there is still some powder lost during AM, the part is printed using just the amount of powder needed (instead of subtracting material from a metal stock). AM also avoids the production of multiple components and the need for joining them together. In consequence, single components can be produced while still meeting the required function (Atzeni, Iuliano, & Salmi, 2011).

This technological benefit is attractive for the aeronautical industry because it helps reducing the buy-to-fly ratio (Mahamood, Shukla, & Pityana, 2014). In fact, the latter is an indicator used to estimate the material losses during manufacturing. It is defined as (Huang et al., 2016) (equation 1):

$$Buy-to-fly\ ratio = \frac{mass\ of\ raw\ material\ needed}{unit\ mass\ of\ finished\ product} \tag{1}$$

The buy-to-fly ratio usually ranges from 12:1 to 33:1 for aircraft parts with CM, and can be significantly reduced (Kianian & Larsson, 2015) if AM is used, sometimes reaching 1:1 (Holshouser et al., 2013). Indeed, the higher this ratio is, the greater material scrap will be generated during production. Keeping this indicator high not only affects the costs and environmental impacts of the production phase (Oak Ridge National Laboratory [ORNL], 2010; Allwood, Ashby, Gutowski, & Worrell, 2011; Dornfeld, 2010; Holshouser et al., 2013), but also those associated to the waste management approach.

Finally, colleagues from our industrial partner, Bell Helicopter, mentioned that AM is useful to answer the fast production of on-demand parts in case of an emergency (for example the replacement of a part in an aircraft). This reduces the necessity to stock parts and eases the logistics of aircraft maintenance.

2.1.6 Environmental and economic assessments of additive manufacturing

The environmental impacts of additive manufacturing have been modelled by some authors (Baumers, Tuck, Hague, Ashcroft, & Wildman, 2010; Kianian & Larsson, 2015; Mognol, Lepicart, & Perry, 2006; Morrow et al., 2007; Yoon et al., 2014). They only consider process parameters such as electrical, material, fluids consumption, thus limiting their studies to one type of resource consumption and disregarding the complete life cycle. Nevertheless, it is undeniable that the efforts to integrate the complete life-cycle are present, although limited (Faludi, Bayley, Bhogal, & Iribarne, 2015; Huang et al., 2016; Paris, Mokhtarian, Coatanéa, Museau, & Ituarte, 2016). Most of these studies consider the environmental aspects of AM and evaluate the potential environmental impacts in order to identify hot spots. Mognol et al. (2006) and Tang et al. (2016) go further in their methodologies by suggesting an iterative optimization of the design process, thus closing the loop with feedback after the environmental evaluation step.

On another hand, the costs of additive manufacturing go beyond the production of parts and can make a real difference in the product design and value chain (Direct Manufacturing Research Centre [DMRC], 2015). In fact, the selection of a part adequate for AM and its design are key parameters which can ensure the economic success of the technology (Lindemann, Jahnke, Moi, & Koch, 2013). Additionally, the life-cycle approach is important in AM in order to inform the designer of the impacts of their decisions on the total life-cycle cost (Reeves & Mendis, 2015). According to Ehrlenspiel, Kiewert, & Lindemann (1998), having a look at the cost of AM is similar to looking at an iceberg: “a customer sees the purchase price as the main criteria, but there are many other aspects where costs occur, for example during the usage of the product”. Other aspects regarding the life cycle are not often considered by customers investing in AM.

Some of the main outcomes of these studies are:

- AM is more advantageous because it gives opportunities to update, repair and remanufacture tooling. The energy consumption may be reduced. AM also enables the reduction of emissions such as CO_2, SO_x, NO_x, CO, PM and the reduction of manufacturing costs (Morrow et al., 2007).

- Topology optimization in AM lowers the fuel consumption and environmental emissions during the use phase because of the possible weight reduction (Huang et al., 2016).
- The AM process is more efficient in terms of material ending up in the final product (Holshouser et al., 2013; Kianian & Larsson, 2015). The resources depletion and the toxicity on human health are reduced because of the lower proportions of metal quantity needed to produce a component. Also, the costs are decreased because of the reduction in manufacturing time (Serres, Tidu, Sankare, & Hlawka, 2011). In addition, because the parts orientation is flexible, many parts can be added on the build platform of AM, thus reducing the costs (Holshouser et al., 2013).
- The costs of AM are reduced when multiple components are printed on the same build plate (Ruffo & Hague, 2007; Yoon et al., 2014). However, it is not convenient for large production volumes when compared to CM (Hopkinson & Dicknes, 2003; Ruffo & Hague, 2007; Massimiliano Ruffo, Tuck, & Hague, 2006).
- One very important parameter in costing is the build time estimated because its significantly impacts the costs of the build job. Three other factors influencing production costs are material costs, machine costs and utilization rate (Brandt, 2016).
- Although inevitable in AM, post-processing steps are often excluded from the scope of these studies. They are significantly influential and could result, with quality control costs, in 50% of the final part cost (Brandt, 2016). In fact, a study has shown that in cases where functional integration is possible, post-processing efforts could be reduced leading to lower costs (Reiher, Lindemann, Jahnke, Deppe, & Koch, 2017). Also, according to Gebbe et al. (2015), cleaning of the parts after the process has been found to be very energy consuming (50% of total energy demand on a production line).
- Because of confidentiality issues, many studies faced the challenge implied by the lack of reliable data which were collected by external LCA experts. In consequence, processes for which not enough practical information was known were modelled using generic data. The results therefore are less representative of the reality.

- No article except that of Mami et al. (2017) combines the LCA with an economic assessment in an eco-efficiency framework. The cost is always integrated in the design process, but not always elaborated from a life-cycle perspective. Nevertheless, post-processing aspects are not considered in Mami et al. (2017) although they affect the eco-efficiency.

2.1.7 Limitations of AM in the aeronautical industry

Although AM has been identified as a sustainable technology compared to CM, Kianian and Larsson (2015) state that more energy is consumed in AM to create the final product when high production volumes are required. Moreover, authors such as Hopkinson & Dicknes (2003), Ruffo & Hague (2007) and Ruffo et al. (2006) have agreed that AM is more efficient in terms of energy and cost at low production volumes compared to CM, where tooling is very expensive. This limits the application of AM to small batch sizes.

Additionally, the AM metal powder is usually more expensive than metal plates or cylinders (Holshouser et al., 2013), setting obstacles to invest in AM technologies. Very often, the production of parts by AM is only prioritized versus CM when the costs are competitive enough or that functional benefits cannot be achieved with conventional methods.

Finally, some safety measures and challenges apply to AM (Pinkerton, 2016). Some materials such as metallic powder should be handled with care (gloves, mask, use of filters), avoiding their contact with contaminants, moisture or excessive light. Moreover, there is a risk of explosion due to possible static electricity and powder in the air. The powder which remains or may be lost (losses are lower than in CM, but are not negligible) from a printing may not be reused because only high quality powder may be required to print parts. The excess material is considered as hazardous waste and should be taken care of to match the properties requirements for recycling. Otherwise, it should be disposed responsibly because of its toxicity (Gibson et al., 2010).

These are few examples showing that AM may not be that more “sustainable” than CM after all. Also, there are many parameters influencing the potential environmental impacts of AM, which may not affect the costs in the same way. In other words, some environmental benefits may imply additional costs and vice versa. It becomes difficult to identify trade-offs when such cases arise.

As a summary of this section, the following needs are identified:

- Account for the complete life-cycle of components in the aeronautical industry, ensuring the approach is relevant for this sector
- Integrate environmental aspects in the early design stages in order to support R&D and have an influence on decision-making
- Elaborate life-cycle environmental aspects in parallel with the costs to ensure a harmonised integration
- Represent trade-off situations between costs and potential environmental impacts

2.2 Eco-efficiency as a tool to support eco-design

This section introduces the eco-design process and some available tools used to integrate environmental aspects into product development. LCA is presented as one of these tools and its limitations are highlighted. Afterwards, the eco-efficiency framework is described to show how environmental and economic dimensions can be combined to support decision-making.

2.2.1 Eco-design definition and procedure

Eco-design is an approach guiding designers or engineers with the implementation of environmental decisions early in the design and development phase of a product. This approach integrates environmental aspects in the design process as one of many other constraints: environmental impacts generated throughout the entire life cycle (from raw materials extraction to the end of life management) are considered. In opposition to traditional design, eco-design aims to improve the environmental performance, i.e. to reduce the damages on the environment that may be caused by the product along its life-cycle (Knight & Jenkins, 2009).

However, efforts must be made to systemically integrate environmental aspects in the traditional design process. To do so, eco-designers usually go through six steps, presented in Figure 2.3 (adapted from ISO/TR (2002) and Lewandowska and Kurczewski (2010)). These steps help conceive systems that meet specific functions, performances and needs (Wood & Greer, 2001). According to Lewandowska and Kurczewski (2010), one of the major steps is planning, during which the input point and target point are defined. The input point definition indicates on the reference object selected (for example an existing product). This starting point represents a basic technological level (technical, functional, cost, social, environmental, etc.), quantified for instance by the assessment of its life-cycle environmental effects (LCA), costs (LCC) and social indicators (Social Life-Cycle Assessment SLCA). The evaluation of environmental effects should result in information about the reference object, the life-cycle stages contributing the most to the environment deterioration, the main environmental issues, and the elements accounted responsible for this degradation.

The target point definition varies whether an entirely new product is designed, or an existing product is improved. The third parties requirements are considered. Afterwards, conclusions and recommendations for the eco-design process are formulated based on the target point definition (for example, steps which should be followed to improve the environmental performance).

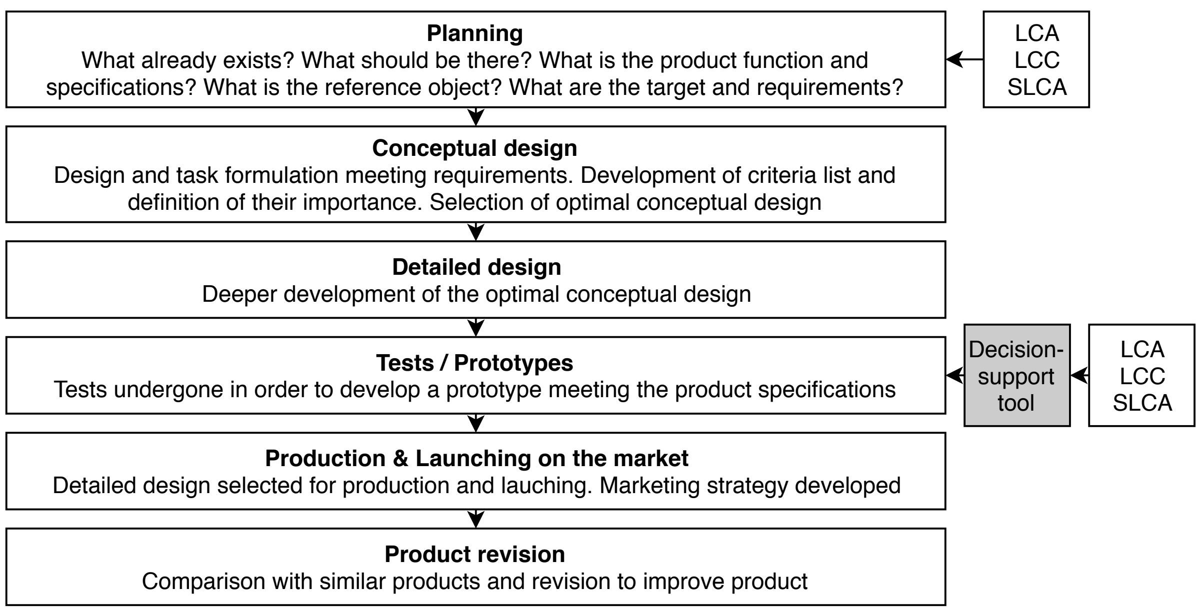


Figure 2.3: Eco-design procedure (adapted from ISO/TR (2002) and Lewandowska and Kurczewski (2010))

The tests and prototypes step is followed by additional assessments aiming to dress a sustainability profile for the suggested detailed designs. These assessments are made to guide the decision and the explicit selection of the design to be produced. This decision results from a transparent response relatively to various requirements and multiple areas of interest (social, environmental, economic, technical criteria, etc.). Nevertheless, it is difficult to decide when there are too many key elements to understand, a wide knowledge of systems design to mobilize, plus a quick and simple approach to adopt. Therefore, there is clearly the need for decision-support tools during the tests and prototypes step of the eco-design process.

In addition, the need to handle the significant uncertainty inherent in the early design stages leads our thinking to the eco-design paradox, elaborated in the following section.

2.2.2 Eco-design paradox

The time spent in the early design stages is significant because design variables are highly uncertain. They depend on the design choices which are influenced by the product needs and requirements. However, the preliminary design stages are key in product development. In fact, it has been shown that the greatest opportunity to improve the environmental performance of a product or service with significant results happens during these stages: 80% of environmental impacts are linked to decisions made during that period (Bhamra et al., 1999; Bhander et al., 2003; Graedel, 1998). Furthermore, these decisions can influence up to 70% of the life-cycle cost (Scaravetti, Nadeau, Pailhes, & Sebastian, 2005; Zimmer & Zablit, 2001). Hence, the capability of reducing life-cycle costs is also possible during these preliminary stages.

Nevertheless, this is contradictory in the way that the preliminary design stages indicate a very limited knowledge of the product. Criteria are usually poorly defined; the possible alternatives for design are multiple and the freedom for improvement is high. Though, the closer we get to implementation (finished product), the more details are elaborated, the lower the freedom of design and opportunities for environmental improvements (Bhander et al., 2003).

This concept is called the eco-design paradox, represented in Figure 2.4 (adapted from Bhander et al. (2003)).

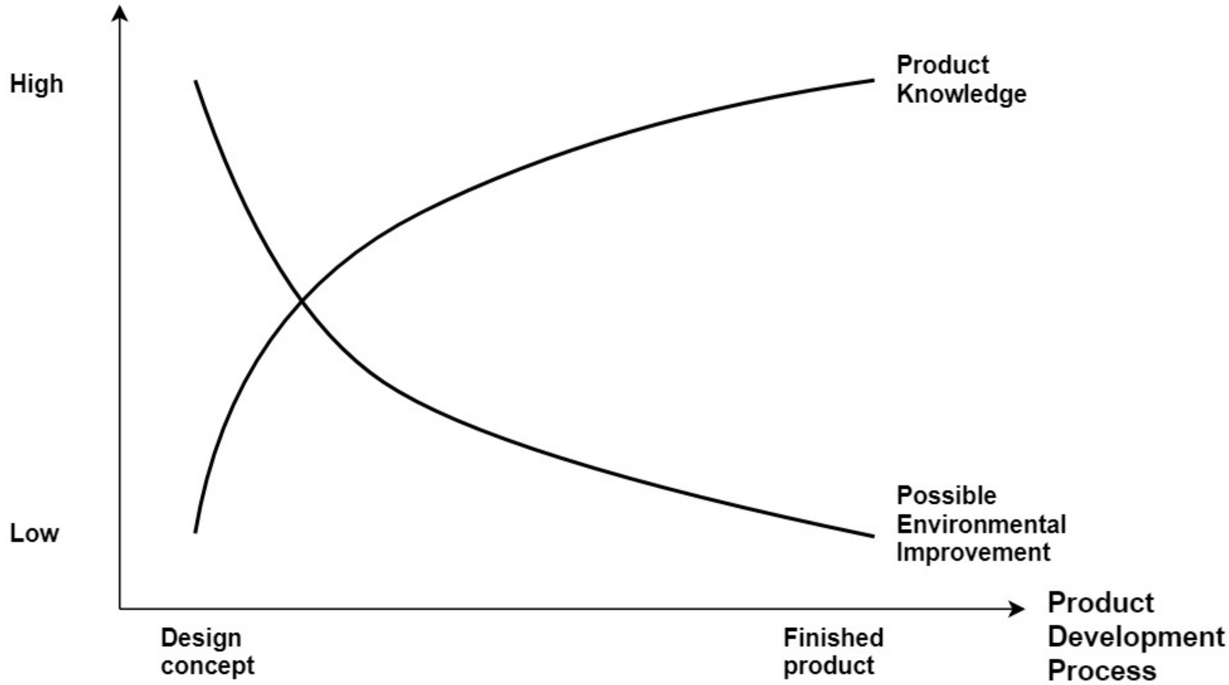


Figure 2.4: The eco-design paradox (adapted from Bhander et al. (2003))

2.2.3 Eco-design tools

Eco-design tools are employed either to *evaluate* or to *improve* the environmental performance of a product, process or service throughout its complete life-cycle. Many authors have listed and classified these tools (Bovea & Pérez-Belis, 2012; Knight & Jenkins, 2009; Le Pochat, 2005; Rossi, Germani, & Zamagni, 2016; Wrisberg et al., 2002). They are usually either distinguished as qualitative or quantitative, and single or multi-criteria approaches.

2.2.3.1 Qualitative tools

They allow users to evaluate and improve environmental aspects of products based on non-detailed information (Bovea & Pérez-Belis, 2012; Knight & Jenkins, 2009; Le Pochat, 2005; Rossi et al., 2016; Wrisberg et al., 2002), and include:

- *Guidelines*, helping through the complete development process, partial or global life-cycle (for example ISO/TR 14062, ISO 14006, Design for X approach) (Rossi et al., 2016). They suggest broad support to improve the environmental profile of a product or service but are too general to help with design choices and decision making.

- *Checklists* are very often used during the preliminary design phases as they allow questions and suggestions to solve problems. They are powerful in the way they emphasize on points requiring attention and avoid missing important information (Wrisberg et al., 2002).
- *Diagrams,* (may be semi-quantitative), include matrices, which usually show in the vertical, the different life stages, and in the horizontal, the human interventions or environmental concerns, such as extractions or emissions, materials choice, energy consumption, etc. They give an overview of the hot spots and highlight opportunities to mitigate the environmental impacts of a product (Material Energy and Toxicity Matrix, Life-cycle design strategy wheel (Brezet, 1997), Environmentally Responsible Product Assessment (Graedel & Allenby, 1995)).

2.2.3.2 Quantitative tools

They enable the quantification of a product environmental aspects. They include broad scope assessments such as the detailed life-cycle assessment, the simplified life-cycle assessment, and assessments focused on single criterion such as carbon or water footprints. Here, the focus is on LCA and simplified LCA.

2.2.3.2.1 Life-cycle assessment

It is a holistic approach which evaluates and quantifies the potential environmental impacts associated with a product, service or process along its life-cycle (ISO, 2006a, 2006b). Thus, it provides an understanding of the complete system and avoids impact displacement. It also supports the decision-making process by identifying hot spots along the life-cycle.

The LCA methodology enables the comparison between different products fulfilling the same function, and is broken down into 4 steps (ISO, 2006a, 2006b):

1) *Goal and scope definition*, to define the product system and its boundaries, the scope and objectives of the study, the functional unit to quantify the performance of the product system. Systems boundaries are either set from cradle-to-gate (raw material acquisition to factory gate), gate-to-gate (from a factory gate to another), gate-to-grave (factory gate to waste management) or cradle-to-grave (raw material acquisition to waste management).

2) *Life-cycle Inventory* (LCI) for the quantification of resource extractions and polluting emissions, in which data related to processes is collected and scaled to the functional unit. Data for elementary flows and product systems may be collected from real case studies or generic databases such as eco-invent (Wernet, 2016).

3) *Life-cycle Impact Assessment* (LCIA) to evaluate the potential impacts linked to emissions. In fact, the inventory data is linked to an impact category through a characterization factor, in order to quantify its contribution to the total value of its impact category.

Several impact assessment methods may be adopted. They vary depending on the geographic context of the study and the environmental mechanisms, cause-effect chains which are accounted for. Also, they depend on the way results are communicated. These may either be presented as midpoints (acidification, eutrophication, ozone depletion, etc.) or endpoints (damages to human health, ecosystem quality, resource consumption, climate change). Endpoints are easier to communicate to an non-LCA expert audience (Kägi et al., 2016). ReCiPe (Goedkoop et al., 2009), Impact 2002+ (Jolliet et al., 2003) and Impact World+ (Bulle et al., 2018) are examples of both midpoint and damage oriented methods.

Furthermore, optional steps in LCIA are grouping, normalization and weighting. Single score weighting may be done depending on the relative importance given to the damage categories, but is not recommended by ISO14044 (2006b) because it implies very subjective choices based on value judgement (Jolliet et al., 2004). In general, there are 5 weighting principles (Goedkoop & Spriensma, 1995): *i) weighting based on social evaluation* (amount of money society is willing to pay for healthcare), *ii) preventing costs* (amount of money to invest in technology to improve processes), *iii) energy consumption* (to remediate to environmental impacts by technical means, for example to purify CO_2 in air), *iv) experts evaluation or panel* (scientists give their judgement based on their experience and opinion), *v) degree to which a target is exceeded* (targets based on scientific data or policies).

The example of ReCiPe (Goedkoop et al., 2009)

This method provides consistent modelling principles and choices, and a harmonised implementation of cause-effect pathways for the calculation of midpoint and endpoint characterisation factors (Goedkoop et al., 2009). ReCiPe considers the knowledge uncertainty of environmental mechanisms, by offering three cultural perspectives (based on differences in choices and assumptions), in accordance with the Cultural Theory by Thompson (1990). First, the Individualist perspective (I) has short-term interest, is optimist, believes that humans can adapt and avoid many problems with the help of technology, and considers only proven effects. The Hierarchist (H) (recommended perspective by the method authors) has an interested balanced between the short and long term which relies on proper policies to potentially avoid problems. The Egalitarian (E) considers the very long term, and all possible impacts even if they are not fully established. Therefore, results will vary with the perspective selected. Europe and the world are the normalization references in ReCiPe; weighting methods applied are experts' panel or the cultural perspectives triangle at endpoints, and prevention costs at midpoints.

One must note that the results representation has underlying uncertainty. It is commonly accepted that as one moves from midpoint to endpoint, the relevance of interpretation increases but the model uncertainty also increases (Weidema, 2009).

4) *Interpretation*, to understand the meaning of results in the decision-making context. This step requires LCA expertise. It includes contribution analyses: these help identify the elements which contribute the most to the environmental impacts. They also help understanding how the impact scores are generated. Sensitivity and uncertainty analyses should be conducted to provide robustness to the results, in other words completeness, coherence, sensibility and quality (ISO, 2006a, 2006b; Jolliet, Saade-Sbeih, Shaked, Jolliet, & Crettaz, 2015).

Nevertheless, LCA requires an extensive and complex analysis of underlying processes, for which data collection is time and resource consuming. This aspect may discourage the willingness to design alternative scenarios (Bhander et al., 2003). Additionally, LCA is usually done to compare the environmental performance of existing or well-defined products at the final stages of product development, making it less relevant for eco-design (Millet, Bistagnino, Lanzavecchia, Camous, & Poldma, 2007). This is why Poudelet, Chayer, Margni, Pellerin, and Samson (2012) suggest using LCA as a prospective tool integrated in the early design stages, i.e. planning, conceptual and detailed design. However, detailed LCA necessitates the understanding of various environmental aspects and is hard to interpret for non-LCA experts (Bhander et al., 2003). This limits its use for designers and for strategic decision-making.

2.2.3.2.2 Simplified life-cycle assessment

Because detailed LCA is less convenient for the technical, strategic and economic aspects of product development (Jolliet, Saadé, & Crettaz, 2010), and because of its complex system modeling, simplified LCA may be adopted to facilitate the integration of environmental impacts in the eco-design process.

Simplified-LCA is easier to develop and focuses on restrained parameters and processes, accounting mainly for hot spots. Simplifications can be made regarding the goal and scope (system boundaries), the life-cycle inventory (parameters and data considered) and the impacts assessment (impact categories presented) (Fugère, 2009; Poudelet et al., 2012).

While remaining consistent and rigorous in the communication and presentation of simplified LCA results (Alton & Underwood, 2003), one must make a compromise between their simplicity and their reliability (Figure 2.5) (Graedel, 1998). In fact, uncertainty levels in simplified-LCA will tend to increase and should therefore be evaluated.

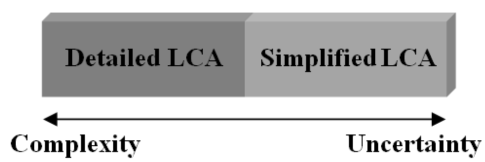


Figure 2.5: Complexity and uncertainty levels for two types of LCA (adapted from Graedel (1998))

In conclusion, LCA is a powerful tool to support eco-design because of its comprehensive approach and inclusion of diverse environmental aspects. It allows the comparison between alternative products. Thus, it provides support in decisions by highlighting improvement opportunities. Yet, none of the eco-design tools, not even LCA, takes into consideration economic aspects. These are primary in product development because the associated costs will directly vary with design choices. As a conclusion, eco-design tools, alone, do not back up decisions from a strategic point of view, and need to be completed by considering costs in an eco-efficiency (EE) framework.

As a summary of this section, the following needs are identified. Some have been addressed by Mami et al. (2017), except for uncertainty evaluation:

- Develop an eco-design approach based on LCA or simplified LCA to quantify the environmental dimension
- Communicate LCA results using indicators which are easy to interpret, and which are relevant to the industry of concern
- Evaluate the uncertainty resulting from the LCA model choices (lacking)
- Integrate cost aspects into eco-design by building on an eco-efficiency framework

2.2.4 Eco-efficiency definition

Comparable to the sustainable development concept, eco-efficiency (EE) was initially intended for the business world in order to “create value while decreasing environmental impact" (Huppes & Ishikawa, 2005a, 2005b; WBCSD, 2000). It considers environmental, economic and social aspects. This means producing efficiently while maintaining a high level of price competitiveness. Also, leading a quality life is important while reducing resource consumption and environmental impacts (Schmidheiny, 1992).

ISO14045 (2012) defines EE as a decision support tool to quantify and relate the value of a product with its environmental performance. It is commonly viewed as a ratio between the economic and environmental performances. Accordingly, the definition given to value is very subjective and specific to the needs of third parties (Huppes & Ishikawa, 2005b). Furthermore, the ISO standard brings guidance to the development of an eco-efficiency assessment. It is described in the following section.

2.2.5 Eco-efficiency framework

The eco-efficiency assessment is broken down into five steps (ISO, 2012): i) goal and scope definition, ii) environmental assessment, iii) product system value assessment, iv) quantification of eco-efficiency, v) interpretation of eco-efficiency.

2.2.5.1 Objectives, goal and scope

As required by ISO (2012), the goal of the study first describes the purpose and objectives of the study, the intended audience and the intended use of results.

2.2.5.1.1 Product systems compared

The product systems compared are described along with the place, time and stakeholders involved in the assessment. One product system is the reference or base scenario, to which alternative scenarios are compared. The product systems are described and compared based on their function and functional unit.

2.2.5.1.2 Function and functional unit

The function identifies in a qualitative way the use of the product. To compare product systems, their function must be equivalent. The functional unit quantifies the function, i.e. it clearly measures the performance of the product system, by scaling the reference flows (quantities of products or services needed) to meet the functional unit.

2.2.5.1.3 System boundaries of the product system

They are equivalent for the environmental and product system value assessment. They are set by defining which life-cycle stage is included or not in the assessment. The inclusion or exclusion of any stage depends on the goal of the study. The assessment can be cradle-to-gate (processes involved for the production of the same product are compared), cradle-to-grave (all processes are compared, from extraction of raw material to end-of-life management), gate-to-gate (only one process in the entire chain is considered and compared), or gate-to-grave (the production and use of the product are the same, only the end-of-life management is compared). When setting the boundaries of the system, the processes which are identical for the compared products can be excluded, only if they do not affect the equivalence between scenarios.

2.2.5.1.4 Allocations to external systems

When a process is multifunctional, it produces more than one product (co-product) or service. Thus, it has more than one function. Consequently, the inputs/outputs must be distributed or allocated to these different functions. The co-products are part of external product systems. These must be identified and the allocation principles applied must align with ISO14044 (2006b).

This means to avoid at first the allocation, by sub-dividing the process into two or more sub-processes. Also, the system boundaries can be extended, by subtracting the avoided effects of a real existing alternative process for the co-product. If the allocation cannot be avoided, then the inputs and outputs must be distributed by taking into account the physical relationships between them. Finally, a mass allocation, economic allocation, or any other type of allocation can be applied. In addition to that, the waste management approach must be specified. The cut-off recycled content approach allocates the recycling process to the system which uses recycled material as an input. The recycling at the end-of-life is excluded from the system boundaries and its impacts are not considered. On another hand, when the recycling is included in the approach, the inputs are considered as 100% raw material. In this case, the recycling process at the waste management step avoids the production of raw material. Its associated impacts can be subtracted (credit is given to recycling). In this case, the allocation principle requires to use substitution and boundary extension.

2.2.5.2 Environmental assessment

As seen previously, there are many existing tools supporting the evaluation of environmental aspects. However, the focus is set here on the Environmental Life-Cycle Assessment (ISO, 2006a, 2006b) because of the holistic vision it enables.

The LCA goal and scope should align with those described in the eco-efficiency framework. Therefore, the environmental assessment starts here with the life-cycle inventory, followed by the impact assessment method. One must note that inventory flows may be used as only input to the eco-efficiency assessment. For example, if a process shows predominant emissions of CO_2 due to fuel consumption, the latter may be used as the only environmental input.

The impact categories and weighting methods should align with the goals of the study and will result in the environmental dimension of eco-efficiency. If several indicators are used, results of eco-efficiency should be considered in parallel. Weighting is not recommended by ISO (2012). Though, if it is used, the weighting principle and factors should be determined.

Indeed, having multiple indicators for the environmental dimension avoids subjective choices and shows a complete environmental profile. However, using them as such for eco-efficiency may tend to confuse the decision-maker, confronted to an additional value indicator. Also, priorities become harder to set when environmental indicators do not have the same trend (they show the same trend if they all describe improved environmental impacts for a scenario compared to another).

Furthermore, because there is no absolute eco-efficiency but rather eco-efficiencies of products compared to one another, eco-efficiency models can be limited considering that both product compared could be "bad". Thus, sustainability would not necessarily be reached (Huppes & Ishikawa, 2005c). For that, Mami et al. (2017) suggest using the distance-to-target weighting approach. The method considers an actual scenario compared to a reference for which environmental impacts are quantified with respect to reduction targets set by the aeronautical industry**.** Indeed, this method accounts only for specific emissions and disregards others emissions which might have significant impacts. Nevertheless, the environmental assessment is more relevant to meet the industry needs and the approach is more probable to be adopted for decision-making. In fact, it is recommended by ISO14001 (2015) to consider products within the environmental policy of enterprises and the objectives and targets of their environmental management system (therefore to analyze impacts linked to a very specific environmental aspect) (ISO, 2015).

2.2.5.3 Value assessment

The value is described as a specific stakeholder value (producer, consumer, investor). Similarly to LCA, it is quantified to meet the functional unit (Wrisberg et al., 2002) defined in the goal and scope of the eco-efficiency framework (ISO, 2012).

The product system value can be monetary (cost, price, willingness to pay, profit, etc.) , functional (performance, product desirability), and of other types (cultural, historical, etc.). In the context of this study, the aeronautical industry wishes to reduce the costs of additive manufacturing compared to conventional manufacturing. Therefore, the monetary value in terms of cost over the complete life-cycle would be the most convenient.

Cost assessment methods have been reviewed by many authors in the literature (Gluch & Baumann, 2004; Hunkeler, Lichtenvort, & Rebitzer, 2008a; Klöpffer, 2003; Wrisberg et al., 2002). However, the environmental Life-Cycle Costing (LCC) (Hunkeler et al., 2008a) is highlighted here because it considers the physical product life-cycle. It broadens the boundaries of conventional life-cycle costing by accounting for the system externalities. Also, it is the most widespread approach for an eco-efficiency context (Kloepffer, 2008). The LCC method analyses the financial flows (internal and external costs) over the complete life-cycle of a product, service or process (Wrisberg et al., 2002). The internal costs are influenced by the market and are directly handled by actors involved in the life cycle, either during production, use or end-of-life. External costs are less predictable because they are not directly paid by a stakeholder; they are priced in monetary units, thus linked to the monetization of social, financial or environmental impacts (Hunkeler & Rebitzer, 2003). The internalization of external costs in an eco-efficiency framework might be considered as double counting since they are a way of expressing environmental impacts.

In general, five stages are included in LCC: research and development, production of materials and components, manufacturing, use phase and maintenance, and end-of-life management. These stages are managed by four actors: materials or component suppliers, product manufacturers, consumers or users and end-of-life actors. Hence, one must describe the life-cycle stages and actors included. The exact timing of LCC in the product development process must be specified. The cost perspective should correspond to the concerned actors.

Also, in an eco-efficiency framework, the system boundaries of LCC must be equivalent to those set in the LCA. For example, environmental LCC may start by considering the R&D phase. The latter may also be included in LCA (for the system boundaries to be identical), but is usually assumed to have negligible environmental impacts (because they can be allocated to a high quantity of products) (Rebitzer, 2002). Elements with a negligible contribution to environmental impacts can be of interest to assess the costs (or vice versa). Hence, they can still be included or excluded from the assessment, as long as they do not violate the condition of boundary equivalence.

While the cost usually accounts for the expenses incurred for a product or service (includes raw material costs and manufacturing), the price translates an aggregation of the upstream costs. Consequently, it can be used when the details on upstream processes are not know (Hunkeler et al., 2008a).

Data collected for the LCA can be used to elaborate the LCC for most of the costs; the physical flows (energy and material) are multiplied by the unit cost paid by the company (Jolliet et al., 2015). Other costs such as labour costs, research and development costs, are handled separately.

Accordingly, to dress the economic inventory, the LCA provides the quantities of flows which are accounted for in the processes of the different product systems. Then, equation 2 below is applied (Jolliet et al., 2015):

$$Cf_i = a_i \times C_u \tag{2}$$

With:

Cf_i : Cost for the flow of input/output i

a_i: Amount of input/output i

C_u: Unit cost of input/output i

Furthermore, the cost model adapted must explain how costs are aggregated (Huppes et al., 2004). Unlike environmental impacts, costs can be summed, and it must be specified if:

- discounting is done, if the cash flows occur at different moments in the lifetime of the assessed product
- the total life-cycle cost required to meet the functional unit is normalized.

Finally, uncertainty should not be neglected in LCC since cost results are highly influenced by the market, the discount rate, the price changes, the competition, the space and time (Schmidt, 2003). Thus, it is important to carry out this kind of analysis to provide consistency to results.

2.2.5.3.1 Discounting

If the system involves costs occurring in the mid-to-long-term future, or at different times within a product life cycle, costs cannot be compared or summed without taking into consideration the value of time. The discount rate can range from 0% to 15% (Hunkeler et al., 2008a) and may be higher depending on the organizations at stake. A sensitivity analysis is recommended to evaluate the influence of applying a discount rate; a critical discussion is recommended if the choice of discounting rate changes the ranking of the compared systems.

2.2.5.3.2 Environmental Life-Cycle Costing for the aeronautical industry

A first traditional structure of cost aligned with the production of AM parts in the aeronautical industry is suggested by (Brandt, 2016) (Figure 2.6). It was strongly influenced by authors such as Ruffo et al. (2006), Hopkinson and Dicknes (2003), Gibson et al. (2010). The author distinguishes three phases: the production costs, the self-costs and the life-cycle costs. The production costs in

Figure 2.7 are useful during the design process to compare alternatives, whereas the self-costs are not always considered for comparison (DIN, 2004; Pahl, Beitz, Feldhusen, & Grote, 2006). In chronological order, production costs are first estimated. Then, based on production costs (because they are the main aspect of decision-making), if AM is still considered as an option compared to CM, self-costs are calculated. Finally, life cycle costs are considered.

Cost calculations are usually based on activities and time. Although this three phases approach seems the most logical and applied in the industry, it is disadvantageous in the way that it does not directly put forward AM as an option for sustainability.

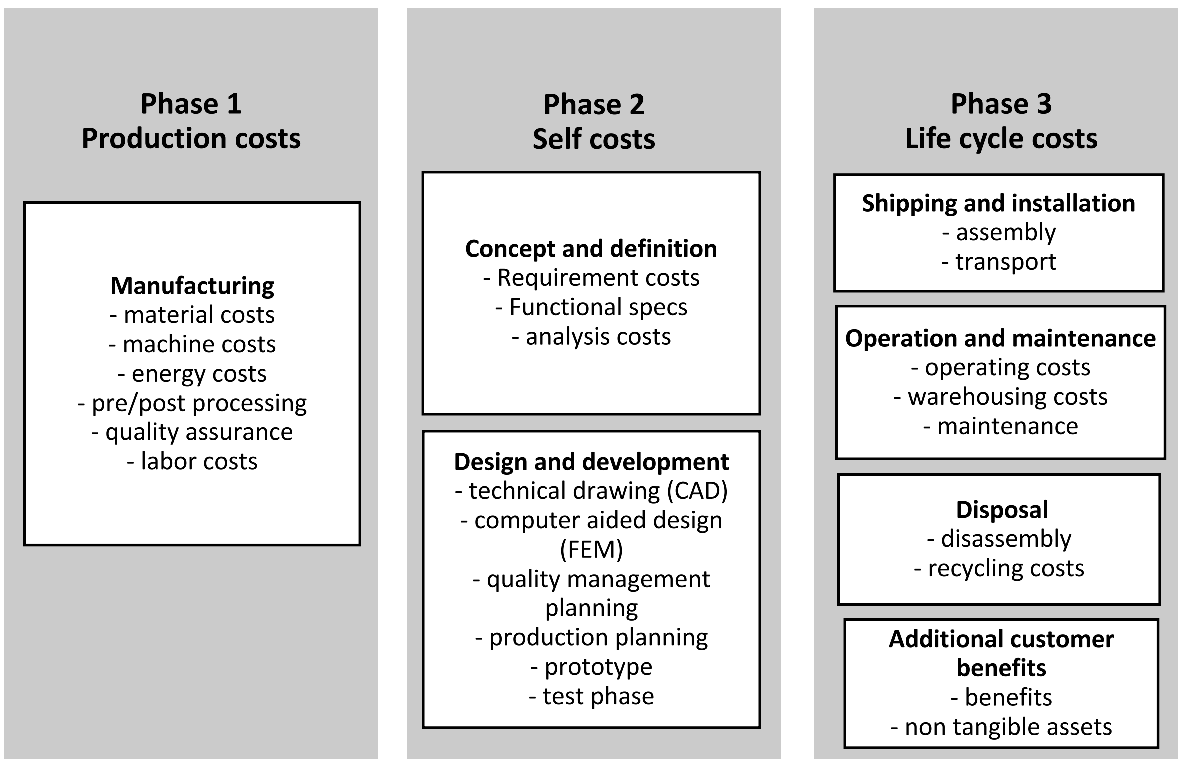


Figure 2.6: Phases of costs in AM lifecycle (adapted from Brandt (2016))

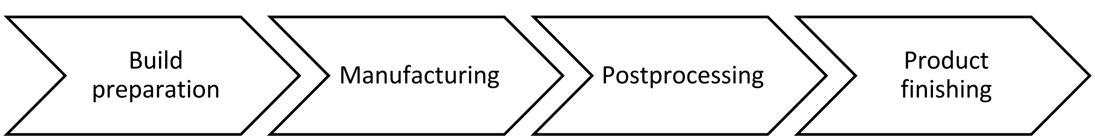


Figure 2.7: Costs during AM production (adapted from DIN (2004); Pahl et al. (2006))

An alternative evaluation of costs for such context is the environmental life-cycle costing (Hunkeler et al., 2008a) developed and adapted by authors such as Khan and Houston (2000), Mami et al. (2017) (Figure 2.8).

Research and development consider the labour hours and tests needed to operationalize the studied system. Production includes direct, indirect costs, and the transport cost from the production site to the assembly facility.

The acquisition cost is the cost of the system before being assembled. If production costs upstream are calculated, the acquisition cost is equal to 0. The assembly accounts for materials, direct, indirect costs, and the transport cost of the system from the assembly site to the operator.

The acquisition cost of the use phase is also equal to 0 if upstream costs are already calculated. During the aircraft lifetime, spare parts are needed for maintenance. Therefore, their production, insurance and storage costs are included. In addition to these, the use phase considers crew cost and the fuel cost due to the weight of the system.

The end-of-life includes waste treatment costs (materials, labour, transport, etc.) and the resale of the system (the latter is considered when system boundaries are extended in the LCA).

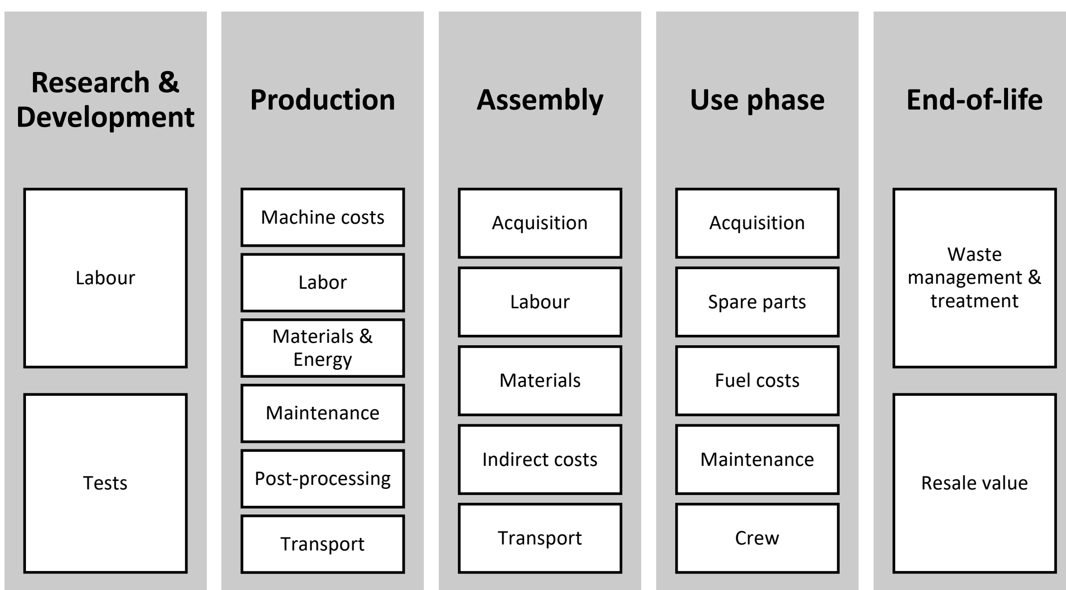


Figure 2.8: Life-cycle costing categories for the manufacturing of aircraft components (adapted from Khan and Houston (2000), Mami et al. (2017))

2.2.5.4 Eco-efficiency quantification

The eco-efficiency quantification indicates on the relationship between the environmental and value assessment results. A product which is more eco-efficient than another should show an improvement on either of the two dimensions (ISO, 2012).

ISO14045 (2012) suggests different methodologies to derive the EE indicator resulting from the combination of both dimensions. It can be applied depending on the study context and objectives. There are three types of eco-efficiency indicators: i) single scores derived from ratios, ii) single scores derived resulting from the sum of indicators, and iii) eco-efficiency profile. They are explained below.

The most common single indicator representation (i) is the ratio of value over environmental impacts, or vice versa depending on the aspect which primes (the product value or the environment) (Huppes & Ishikawa, 2007). Environmental impacts presented through multiple indicators will result in more than one eco-efficiency indicator. Another example of a single score indicator is the “Factor-X”. It is the ratio of a product eco-efficiency to that of another compared product. However, this ratio is criticized because both product may have very low absolute eco-efficiencies. Hence, the eco-efficiency is not necessarily improved with respect to greater sustainability objectives (Bjørn & Hauschild, 2013). Nevertheless, ISO14045 (2012) does not restrict the use of ratios. Yet, they must be interpreted with care because they do not show variations of both dimensions distinctly and might lead to confusions.

Moreover, single scores can be derived from the monetization of environmental impacts or a weighted sum (ii). Finally, the eco-efficiency profile (iii) is an XY diagram that allows the distinction between both the value and environment dimensions and is therefore more transparent when trade-off situations arise.

Specifically to answer the needs of the aeronautical industry, the eco-efficiency indicator suggested by Mami et al. (2017) is based on the concept of getting closer to the objectives set by the industry. In other words, the distance between the current and target state must be minimized. Thus, the indicator is calculated as the sum of the normalized environmental impacts and the product between the normalized cost and the trade-off value (refer to equation 17 in section 4.4.9). The normalization reference is an aircraft life-cycle impacts and costs. The trade-off value is subjective. It expresses the compromise one is ready to make between the damages to the environment and the costs. The highest eco-efficiency indicator represents the most eco-efficient alternative.

2.2.5.5 Eco-efficiency interpretation

The eco-efficiency XY diagram (Figure 2.9) enables the distinction between both dimensions. It helps identifying possible trade-offs. The environmental assessment generates an impact score, whereas the environmental LCC generates a cost. Afterwards, the normalization is done to obtain dimensionless values, making it possible to place them on an eco-efficiency graph using the same scale for both axes. For the aeronautics context example, both dimensions would be expressed as percentages of increase or decrease of the aircraft life-cycle cost/impact. The diagram is explained below.

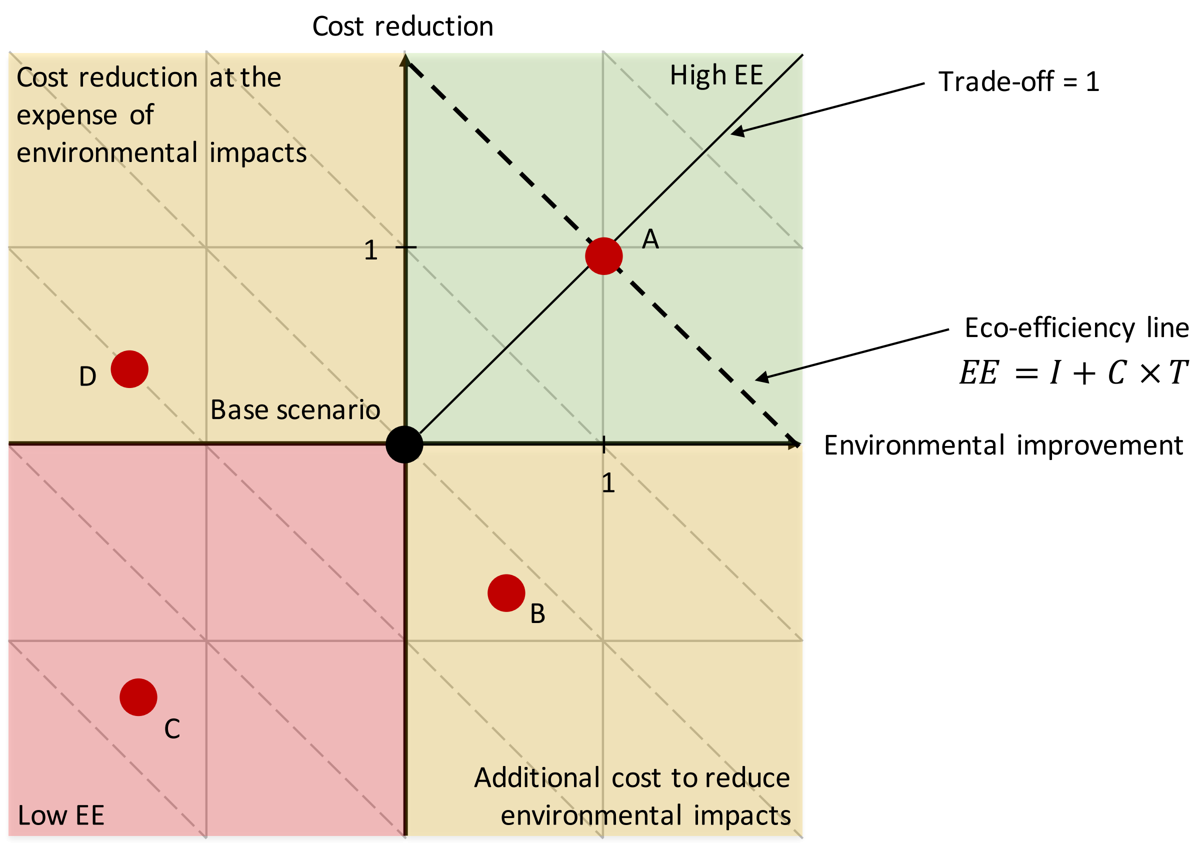


Figure 2.9: Eco-efficiency diagram

The representation based on the work of Mami et al. (2017) evaluates the distance between the reference (or base) scenario and an alternative. The distance, for the economic dimension, is defined as the difference between the cost of the reference scenario and that of an alternative: a positive score shows a cost reduction for the alternative compared to the reference. Similarly, the difference between the environmental impact of the reference scenario with the alternative is calculated: a positive score shows an environmental improvement.

The dotted lines represent iso-eco-efficiency lines for a trade-off of 1, meaning that all scenarios located on the same line have an equivalent eco-efficiency. They will be more eco-efficient than any other scenario located under the dotted line. A trade-off of 1 means that the cost reduction and environmental improvement have the same importance in decision-making.

Nevertheless, three cases are addressed when comparing eco-efficiency assessment results (ISO, 2012): i) improvement or superiority in both dimensions (economic and environmental), ii) improvement or superiority in only one dimension, iii) no improvement or superiority in either dimension.

- Scenario A is in the upper right side of the diagram: it has a high eco-efficiency compared to the base scenario. Also comparing it to scenarios B, C and D, it dominates (or is superior to) them all, i.e. it has a more significant cost reduction and environmental improvement.
- Scenario C is in the lower left side of the diagram: it has a lower eco-efficiency compared to the base scenario (it is worse on both dimensions and should directly be eliminated).
- Scenario B is in the lower right side of the diagram, and scenario D is in the upper left side of the diagram: they both are examples of trade-off situations compared to the base scenario. Following the iso-eco-efficiency dotted line, the base scenario is more eco-efficient than B, C and D. Scenario B, however, shows an improved environmental profile compared to the base scenario. Although its cost is higher, ISO14045 (2012) recommends that scenario B be claimed more eco-efficient than the reference, because it demonstrates an improved environmental performance.
- While Scenario D shows a more significant cost reduction than the base scenario, it should be eliminated because the cost reduction is at the expense of the environment (ISO, 2012).

- The base scenario and scenario B have an equivalent eco-efficiency for a trade-off of 0.5 (Figure 2.10). In other words, B is more eco-efficient than the base scenario if the environmental dimension is at least two times more important than the cost.

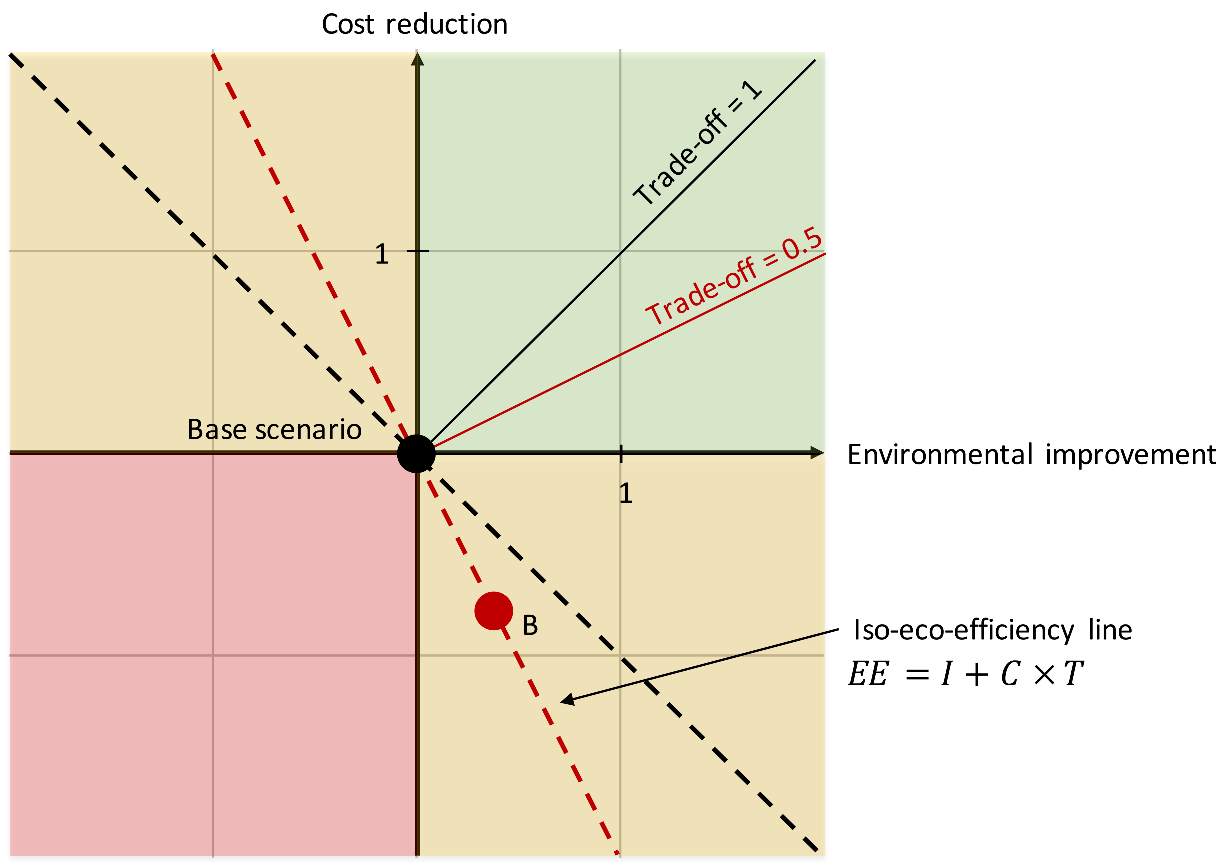


Figure 2.10: Eco-efficiency diagram with trade-off situations

ISO14045 (2012) recommends completing the eco-efficiency assessment with an evaluation of the completeness, sensitivity, uncertainty and consistency of the results. Also, in this step, the conclusions, limitations, and recommendations should be discussed.

2.2.6 Limitations in the eco-efficiency framework

The conclusions of Mami et al. (2017) have proven, using “one-at-a-time” sensitivity analyses (one parameter at a time is changed to see how it influences the outcome result), that parameters included in the LCA, LCC and eco-efficiency models could significantly change conclusions. In such complex models, there is clearly the need to evaluate the influence of a wider set of parameters varying at the same time. It is also essential to evaluate the reliability of results and conclusions, by communicating the uncertainty of deterministic results.

Additionally, cases might arise where two scenarios seem to be very close to each other on the eco-efficiency diagram. This limits the results interpretation: one can't really tell if one scenario is significantly more eco-efficient than another in order to make a decision. This will mostly be true if there is indeed an environmental improvement, but it is not significant enough to convince the decision-maker when additional costs are at stake.

ISO14045 (2012) recommends undergoing an uncertainty assessment to complete the eco-efficiency framework, by assessing the precision, completeness and representativeness of the results. Additionally, the standard suggests evaluating the significance of the differences found between scenarios. Nevertheless, among all the studies reviewed and to the best of our knowledge, only Faludi et al. (2015) and Mami et al. (2017) carried out sensitivity and uncertainty analyses. Yet, none have evaluated it in a probabilistic approach. Also, to the best of our knowledge, no article was found regarding uncertainty representation in eco-efficiency diagrams.

As a summary of this section, the following needs are identified:

- Evaluate the uncertainty in the LCA and LCC quantitatively to increase the confidence given to results, using probabilistic approaches
- Combine these uncertainty assessments to obtain the uncertainty of the eco-efficiency indicator
- Represent the resulting uncertainty on the eco-efficiency XY diagram
- Evaluate the significance of the difference between scenarios in order to support decision-making

2.3 Uncertainty in eco-efficiency and decision-making

As shown in the previous section, the eco-efficiency framework needs to be improved to support decision-making. This section presents how eco-efficiency as a decision-aid tool can be improved by accounting for the uncertainties. It also highlights existing methods to handle uncertainty.

2.3.1 Importance of knowing uncertainty

The LCA and LCC methods result in deterministic values assigned to two distinct scenarios (or more), such as those presented at the left the figure below.

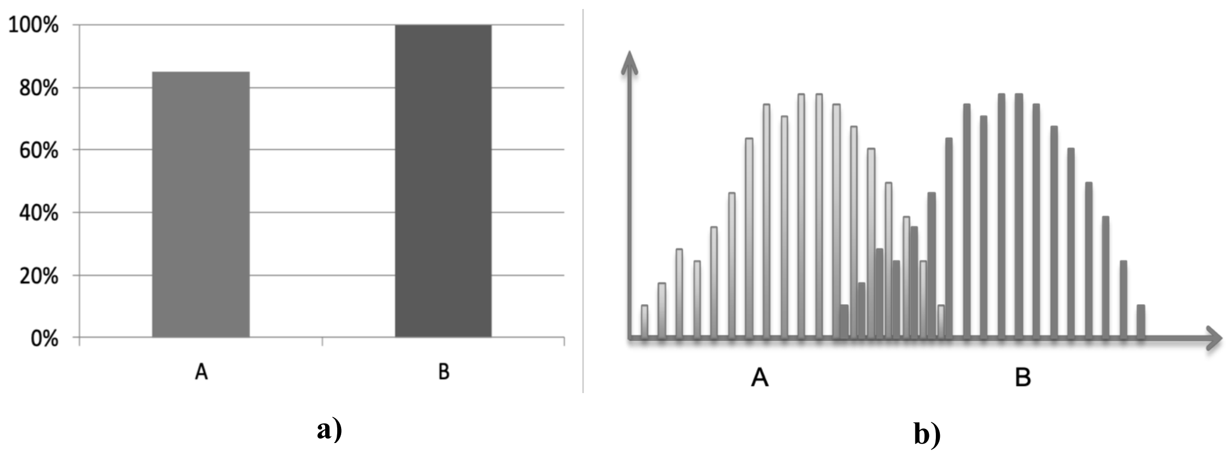


Figure 2.11: Deterministic (a) versus probabilistic (b) scenarios

If scenario A and B are either compared in terms of environmental impacts or costs, the deterministic results at the left do not indicate to which extent A is better than B. Analyzing uncertainty in such assessments should support decision-making by determining the significance of difference between these two scenarios. This is possible with stochastic representations supported by statistical tests: the probability that a scenario is better or worse than another may be evaluated (figure on the right). These outcomes in greater confidence given to statements and conclusions. In fact, if the uncertainty is ignored, misguided decisions may be encouraged (Budnitz, Apostolakis, & Boore, 1997).

LCA is a simplified, known, predictable model used to represent the reality in a decision-making context. In general, there are three principal issues facing the decision-maker (Morin, 2017; Patouillard, 2018): (i) the problem complexity (multiple considered dimensions), ii) the uncertainty (inherent to unknown consequences of decisions), and iii) the issues and challenges (importance of decision consequences on several aspects of society). According to Patouillard (2018), problem complexity in LCA is found in results uncertainty affecting decision-making and the priorities setting with respect to the protection of human health and the environment. Hence, reducing uncertainty in LCA is important to lower decision uncertainty and the risk of omitting an environmental aspect (due to its significant uncertainty).

Therefore, supporting decision-making means providing transparent and robust results to third parties to help them make informed choices depending on their priorities and preferences. This is usually ensured by delivering precise (reliable) and accurate (representative) results (Brandão, Clift, Cowie, & Greenhalgh, 2014) (Figure 2.12).

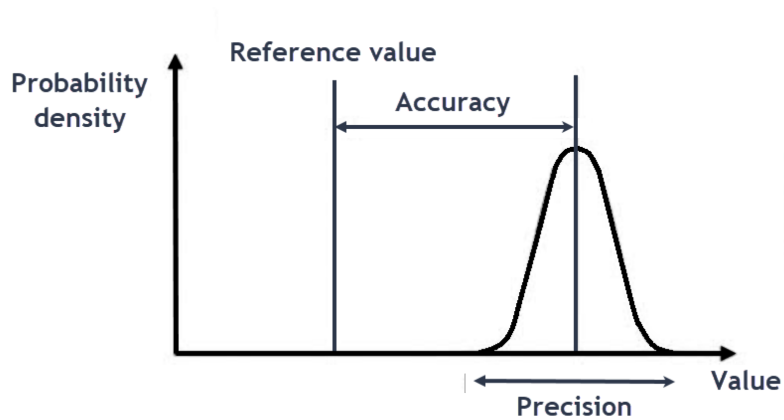


Figure 2.12: Distinction between precision and accuracy (adapted from Brandão et al. (2014))

2.3.2 Uncertainty types and sources

There are two types of uncertainty found in LCA (Huijbregts, 1998) and presented in Figure 2.13. *Aleatory or stochastic uncertainty* (called variability in LCA), is inherent to variations in the real natural world which are out of our control as humans. They can't be reduced (temporal, spatial, between sources and objects). *Epistemic uncertainty* (called uncertainty in LCA) derives from our lack of knowledge about the true value of a quantity (parameter, scenario, model, inaccurate measurements, lack or irrelevant data, assumptions, etc.). It results from our limited capabilities to perfectly measure and model our surrounding world (Li, Chen, & Feng, 2013; Steinmann, Hauck, Karuppiah, Laurenzi, & Huijbregts, 2014).

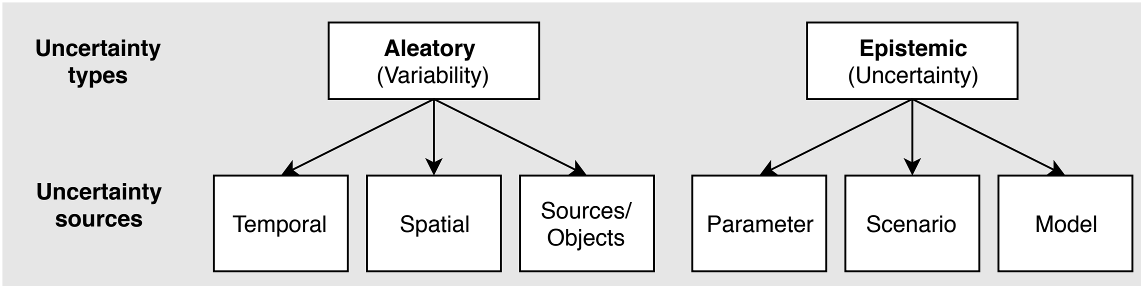


Figure 2.13: Uncertainty types and sources

In LCA, only uncertainty resulting from the lack of human knowledge may be reduced. It is treated by the theory of possibilities, based on the apparition probability of an event as per our knowledge of it. Therefore, a specific focus will be set on epistemic uncertainty here.

As part of epistemic uncertainty, parameter uncertainty is derived from the lack of knowledge on the exact value of a parameter, whereas scenario uncertainty is associated with choices in the LCA model construction. Finally, model uncertainty derives from simplifications and assumptions made in the model about its validity in the real world (Huijbregts, 1998). These three uncertainty sources are difficult to differentiate because they overlap (Gregory et al., 2017). Thus, they are often aggregated and expressed using the uncertainty on a parameter value (De Koning, Schowanek, Dewaele, Weisbrod, & Guinée, 2010).

2.3.3 Uncertainty evaluation

2.3.3.1 Distinction between interaction and correlation

As mentioned by Patouillard (2018), interactions between input data in LCA should be distinguished from correlation. Both should be taken into account in uncertainty and sensitivity analyses in order to avoid biased results (Groen, Bokkers, Heijungs, & de Boer, 2017). While interactions describe the causal relationship within a model, correlation shows to which extent the link between variables is strong (a similar variation tendency, i.e. strength and direction of relationship, will indicate a strong correlation). The interaction degree within a model is defined by the maximum number of variables being multiplied. In LCA, multiple input variables are correlated and are described by high number of interactions (relationship between intermediary flows, elementary flows, and characterization factors).

2.3.3.2 Measuring uncertainty: uncertainty and sensitivity analyses

Uncertainty and sensitivity analyses are both examples of uncertainty evaluations that "shall be conducted for studies intended to be used in comparative assertions intended to be disclosed to the public" ISO14044 (2006b). Uncertainty analysis is conducted to inform the decision-maker on the conclusions degree of certainty, whereas sensitivity analysis helps identifying parameters with the most significant influence on results uncertainty.

2.3.3.2.1 Uncertainty analysis in LCA and LCC

Evaluating uncertainty in LCA usually focuses on statistical approaches to quantify uncertainty in a reasonable time (Heijungs & Huijbregts, 2004; Patouillard, 2018). If a statistical approach is not possible, qualitative (expert judgement) or semi-quantitative (Pedigree) methods can be applied.

Existing studies in the literature have focused on uncertainty in LCA (Gregory et al., 2017) and LCC (Battke, Schmidt, Grosspietsch, & Hoffmann, 2013; Gregory et al., 2017; Ilg, Scope, Muench, & Guenther, 2017).

Statistical methods are broken down into three steps: i) input, ii) propagation, iii) output. One very well-known example is the Monte Carlo analysis. It is a sampling method which computes repeated calculations in order to generate probabilistic results. In other words, probability density functions are used to define input parameters. Afterwards, the model runs for a specific number of times, resulting in a distribution of outcomes (Heijungs & Huijbregts, 2004). The higher the number of iterations, the more statistically significant the outcome. Nevertheless, calculations can become very time-consuming if the number of input parameter is high.

An illustrative example for conducting probabilistic LCA and LCC assessments was found in the literature (Gregory et al., 2017). The authors suggest the following steps:

i. *Identify uncertain parameters* and categorize them as empirical (measurable with a true value, for example quantity of material input), model domain (appropriate value aligned with the scope, for example product lifetime) and value parameters (appropriate value aligned with the preferences of analyst, for example, discount rate). The categorization is not necessary.

ii. *Characterize uncertainty:* weighted probability distributions (normal or lognormal) are used to represent empirical quantities (because they have a true value), from measurements and data estimates, whereas ranges of continuous or discrete values with equal likelihood (unweighted or uniform distribution) are used for model domain and value parameters, because there is a lack of knowledge on the likelihood of quantities (Gregory et al., 2017). Minimum, mean and maximum values may be used to derive the distributions (Battke et al., 2013). It is important to note that the shape of the input distribution highly influences the probabilistic method outcomes (Boussabaine & Kirkham, 2008).

In cases where there is not clear value or distribution for a parameter, Gregory et al. (2017) suggest defining a rough distribution although increasing the tendency to overestimate uncertainty. If this parameter highly influences the outcome, discrete scenarios may be defined within a uniform distribution.

The characterization of initial and future costs is important because they are influential (Gregory et al., 2017); forecasting techniques may be used to estimate prices and their probabilistic uncertainty (Swei, Gregory, & Kirchain, 2016).

iii. *Conduct and interpret uncertainty analysis* by comparing products under uncertainty. The probability of a scenario being better than another may be evaluated using multiple comparison metrics (Gregory et al., 2017): the difference between the mean value of two compared scenarios, the difference between their 90th percentile or the frequency that a scenario has a lower impact or cost than that of another scenario.

2.3.3.2.2 Sensitivity analysis in LCA and LCC

Sensitivity analysis evaluates the effect of a choice on the outcome. The latter may be either a result or the uncertainty of a result (therefore called contribution to uncertainty). The choice of a continuous parameter (mass of component, emission, characterization factor) helps answering the question: How do a change in parameter value affect the outcome? The choice of a discontinuous parameter (allocation method, characterization approach) helps to show how a change in model or scenario may affect the outcome.

Several types of sensitivity analyses may be carried out to identify key parameters affecting results uncertainty (Borgonovo & Plischke, 2016). Here, the local sensitivity analysis is distinguished from the global sensitivity analysis.

Local sensitivity analysis is a deterministic approach carried out to understand the influence on the results of slight input data variations. Most approaches are "one-at-a-time" techniques (Borgonovo & Plischke, 2016), where we vary one parameter value (deterministic) while keeping all other parameters value constant. Results are calculated and compared to the baseline results in tornado diagrams; the greater the difference, the higher the sensitivity. This is done for each parameter, one at a time, and usually requires expert judgement for the choice of parameters. For discontinuous parameters, discrete scenarios should be compared. Nevertheless, local sensitivity analyses are recognized as "flawed" because they fail to consider interactions and correlations between parameters (they assume the effect is linear). Also, they are based on subjective choices, shedding the light upon a few parameters and disregarding others that could still affect the outcome.

Global sensitivity analysis (GSA) is a probabilistic approach which considers the complete input parameter set, by defining probability distributions to each of them.

Existing methods to perform GSA in LCA can be broken down into three categories (Borgonovo & Plischke, 2016): analytical methods, methods based on correlation, and methods based on the output variance. According to Groen et al. (2017), for most of the methods they consider, "it is not known under which conditions they perform optimally or if a method performs better than another in LCA".

The focus here is to advance correlation methods because they address sensitivity indicators which can directly be generated from Monte Carlo simulations. Two examples of correlation methods are: i) Pearson product moment correlation and ii) Spearman rank order correlation.

The Pearson product moment correlation evaluates the linear relationship between two continuous variables (Minitab, 2017), i.e. the change in one variable is proportional to the change in the other variable. It is not convenient for non-linear models.

The Spearman rank order correlation describes a monotonic relationship between two variables, i.e. variables change together but not necessarily at a constant rate. It considers the ranked values instead of raw values (as in the Pearson product moment coefficient). It is convenient for non-linear models (Altman & Krzywinski, 2015) and is said to perform best when the input uncertainty is large (Groen et al., 2017). Nevertheless, conclusions derived using this coefficient might be misleading because low effect may be over-estimated when interactions between variables are high (Saltelli, Tarantola, & Chan, 1999).

2.3.3.3 Limitations of uncertainty assessment for eco-design

Uncertainty assessment is needed to provide decision-makers with a measure of the confidence levels given to the results. It avoids misleading conclusions (Refsgaard, van der Sluijs, Højberg, & Vanrolleghem, 2007). Also, according to Hare, Cope, & Warde (2015), uncertain data is important to guide good decisions in the early design stages of the eco-design process. This is possible using appropriate data and tools which offer proper and useful guidance without requiring excessive efforts.

Despite the imprecision and inaccuracy of data, firm conclusions can be done if uncertainty is communicated along with the probability of a scenario being better than another (if a statistical approach is adopted). In other words, products can be compared under uncertainty, by showing the percentage of Monte Carlo iterations where one alternative has a lower outcome than that of another product it is compared to (Gregory et al., 2017; Lesage, Mutel, Schenker, & Margni, 2018; Mattila, Kujanpää, Dahlbo, Soukka, & Myllymaa, 2011). Indeed, “uncertainty does not tell us that we are right but the chances of being wrong” (Krzywinski & Altman, 2013). Therefore, the decision remains in the hands of the decision-maker. Yet, it will be more informed and robust and will help managing the risk of the eco-design approach.

The need for ease-of-use, simple and time-efficient calculations for eco-design tools have been identified by Lesage et al. (2018). However, as seen previously, one challenge of treating uncertainty by sampling methods is to provide data on the probability distributions of input parameters. This information is not always available, yet could be provided using the Pedigree approach (Weidema & Wesnaes, 1996). Also, in comparative LCA, inventory flows or LCIA scores of aggregated datasets are usually presented using probability distributions that account for the uncertainty of underlying parameters in the technology and environmental matrices. Though, it implies that the distributions of the aggregated datasets are independent while they usually aren't. As a solution to this issue, the use of pre-calculated stored Monte Carlo simulation results, rather than the use of distributions, is suggested by Lesage et al. (2018). The authors’ approach consists in building a database of presampled aggregated datasets that are stored in a given order to account for dependencies. In other words, it means that:

- They work on terminated LCI datasets, i.e. aggregated system processes (cradle-to-gate) which do not give access to information on the links between activities in the processes. Aggregated system processes, opposed to unit processes, mask information and do not provide an understanding of the underlying structure and model of the LCA (Broadbent et al., 2011). Nevertheless, they preserve data integrity and increase calculation efficiency.
- The precalculated results can be stored in eco-design tools, to increase the calculation speed without doing deep analyses of product systems (unit process data would be required). They can easily be used by non LCA experts. Finally, they avoid the need to solve the large system of linear equations usually required in an LCA, because the aggregated datasets are based on the solutions to this system (Lesage et al., 2018) (expressed as LCI with g or LCIA with h).

$$A \times s = f \tag{3}$$

$$g = B \times s \tag{4}$$

$$g = B \times A^{-1} \times f \tag{5}$$

$$h = c \times B \times A^{-1} \times f \tag{6}$$

Where:

A: technological matrix, i.e matrix with inputs/outputs from/to the technosphere

s : Scaling vector

f : Demand vector

g: Life-cycle inventory vector

B: Environmental matrix, i.e. matrix vith inputs/outputs from/to the environment

h: Impact score vector (for a given impact category)

c: Characterization factors vector

First, the number of iterations n is specified. The end result of the code is n LCIA results for a specified number of final demands (i.e. number of products for which aggregated datasets are required; products are converted into final demand vectors) and LCIA methods. For each Monte Carlo iteration, random values are sampled for A and B based on their probability density functions. Then, the LCI is calculated for each final demand using equation 5. The resulting LCI vectors are piled in order and their dimension is equal to the product of elementary flows in the database and the number of iterations n. The LCIA array can be derived from the LCI using equation 6, choosing a specific number of impact categories (depending on the LCIA method chosen and the characterization factor vectors). This results in arrays of one dimension containing n cradle-to-gate LCIA scores.

To sum up, the results are precalculated Monte Carlo iterations; each Monte Carlo iteration uses the same samples for parameters from matrices A and B (Figure 2.14, personal illustration). Accounting for dependent sampling is important and more pronounced when high correlations exist within the model.

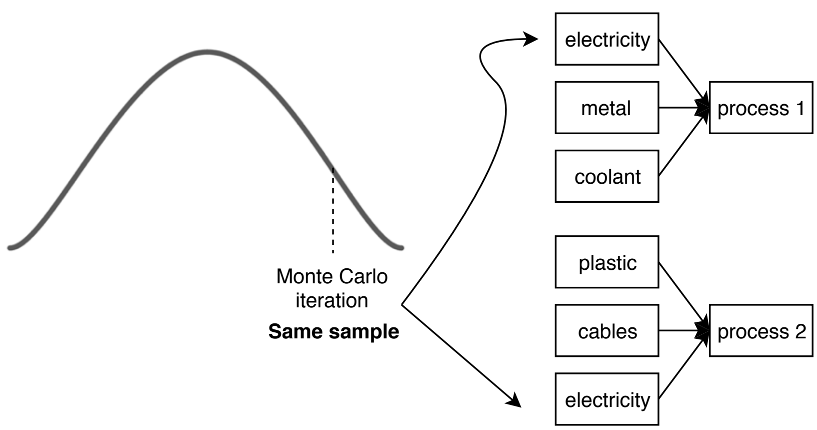


Figure 2.14: Dependent sampling

2.3.3.4 Uncertainty in LCA and LCC for the aeronautical industry

Most of the existing studies on LCA, LCC and eco-efficiency for additive manufacturing in the aeronautical industry have been reviewed. The degree of variability in technological, environmental and economic data is found to be high. It is also the case for the variability of input parameters taken into consideration. However, a systematic assessment of the underlying uncertainty is lacking. Additionally, uncertainties in LCC have a strong influence on results when long time horizons are considered (Ammar, Zayed, & Moselhi, 2012). Therefore, the credibility of LCC results may be questioned (Ilg et al., 2017). This could be the case for the aeronautical industry, where aircraft and products lifetimes are significant. As a summary of this section, the following needs are identified:

- Facilitate the integration and handling of uncertainty in eco-design tools in order to make them easy to use by non LCA experts
- Evaluate the uncertainty in LCA, LCC and eco-efficiency results to support decision-making
- Adopt an approach based on global sensitivity analysis in order to account for the wide set of parameters within the LCA, LCC and eco-efficiency models
- Compare products under uncertainty by showing the probability of a scenario being better than another, and support decision-making by communicating uncertainty levels
- Show the contribution of these parameters to the overall uncertainty, in order to identify where to put efforts to reduce uncertainty and refine data collection.

CHAPTER 3 PROBLEM STATEMENT AND OBJECTIVES

In the context of the Manu-710 project involving industrial partners from the aeronautics and manufacturing sectors, the need to acknowledge the real benefits of AM compared to CM was met by considering the environmental dimension of these technologies. “Easy-LCA”, a simplified LCA tool, was developed by CIRAIG (2018). Its aim was to help industrial partners understand the underlying potential impacts of these two technologies, in order to support decision-making in the detailed design phase. Also, this tool was developed to help them reduce their environmental impacts to meet the reduction targets set by the aeronautical industry. The potential environmental impacts were presented using IMPACT 2002+ (Jolliet et al., 2003), in terms of damage to human health, ecosystem quality, resource consumption and climate change. However, these four indicators are likely to make difficult the results interpretation and the industrial partners decisions. This is because the results do not necessarily have the same trend (i.e. one scenario can show lower impacts in terms of CO_2 eq compared to another scenario but additional impacts in terms of DALY-Disability Adjusted Life Year). Although industrial partners may be comfortable enough with the term “kg CO_2 eq”, they are not very familiar with units such as DALY, PDF.m^2.yr (Potentially Disappeared Fraction of species over a certain amount of m^2 during a certain amount of years) and MJ (Mega Joules- amount of energy extracted or needed to extract the resources). In general, the complexity of LCA indicators limits its implementation in the early design stages. Moreover, the aeronautical industry has set reduction targets for emissions of CO_2, NO_x and PM. Thus, the focus is shifted to consider these emissions only, in order to stay relevant to the needs of the industry.

Because we are dealing with the detailed design phase of product development, environmental aspects may be addressed using an eco-design approach. However, environmental impacts are rarely included in decision-making at the early design stages because the cost is predominant in strategical decisions. Decision-making becomes difficult when combining both worlds. This is true in the context of parts produced by AM for the aeronautical industry: the technology presents trade-offs between the cost and the environment. Thus, in order to use LCA in a prospective and efficient way, environmental aspects need to be elaborated in parallel with the costs to ensure a harmonised integration and an influence on decisions. The eco-efficiency approach developed by Mami et al. (2017) has proven to consistently and systematically combine both dimensions.

Moreover, cost analyses elaborated by profit-making enterprises in the aerospace industry do not necessarily take into consideration the costs over the complete life-cycle. Hence, the global benefits of AM are not highlighted. For example, production costs of AM due to the machine and material costs are high. Yet, they can be offset during the use phase of the airplane, because of the fuel consumption reduction. This clearly emphasizes the need for a life-cycle perspective of costs.

On another hand, at the detailed design phase of product development, the uncertainty is high. There is no way of ensuring that the initial product designed will be the same as the one launched on the market. Also, LCA has been used in most of the cases as a retrospective tool, comparing products only once they have already been launched. This is mainly due to time and resource consuming efforts to model the systems and is a strong limit of LCA. It can be palliated using simplified LCA. Nevertheless, the former may be developed at the expense of an increased uncertainty. If this uncertainty is not evaluated in the early-design, decision-making may be misguided because of erroneous results interpretation. In fact, each of the LCA and LCC models leads to uncertainties: the uncertainty of data collected, the uncertainty of generic processes used from databases, the uncertainty of parameters, scenarios and models selected, the uncertainty of impact assessment methods and finally the uncertainty of weighting and value choices. These are moreover increased by the uncertainty of the eco-efficiency model (normalization references, reduction targets). Among all of the studies reviewed on environmental and economic aspects of AM, none evaluates the uncertainty systematically. Also, to the best of our knowledge, no study has addressed uncertainty representation in eco-efficiency diagrams. This gap in the literature needs to be filled by quantifying uncertainty in LCA, LCC and eco-efficiency for communication purposes. In fact, doing so provides transparent and robust results to the third parties. This will help them make informed choices, depending on the confidence given to results. Communicating uncertainty would also indicate whether or not the uncertainties are high to the point that no conclusions or decisions can be made. Furthermore, the uncertainty assessment needs to evaluate the probability that a decision is wrong. It should also help identifying the parameters which contribute the most to the results uncertainty. This would highlight where to focus data collection efforts.

Objectives definition

The general objective of this project is to integrate uncertainty knowledge into an eco-design approach built on the eco-efficiency concept, in order to help industrial partners make informed and robust decisions from a life-cycle perspective. This approach is built around a case study on additive manufacturing applied to the aeronautical industry.

This general objective is based on the following research questions:

1. How can the confidence level and robustness of eco-efficiency results be evaluated?
2. How can eco-efficiency be used to improve the eco-design of AM parts in the aeronautical industry?
3. How can transparency be increased and data collection efforts guided for eco-efficiency and decision-making?

In order to answer these questions, specifics objectives are defined:

1. Develop a stochastic eco-efficiency approach to evaluate the confidence level given to eco-efficiency results, building on the eco-efficiency framework of Mami et al. (2017) and by filling gaps found in their environmental and cost models (refine use phase data, improve production costs modelling, include post-processing steps).
2. Develop the eco-efficiency approach for AM of aircraft components, by accounting for the needs and targets of the aeronautical industry, and evaluate the eco-efficiency of different design alternatives.
3. Identify the major uncertainty contributors in order to refine data collection and decrease the uncertainty of decisions.

CHAPTER 4 METHODOLOGY AND CASE STUDY

4.1 Overview

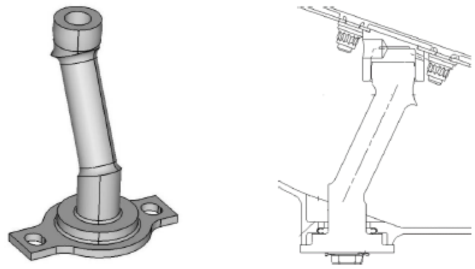
The methodology is developed around a case study about the design of an aircraft engine component by conventional and additive manufacturing technologies. The aim is to compare them, assess their environmental and economic performances, and identify improvement paths for research and development.

The methodology builds on the ISO 14045 (2012) framework on eco-efficiency analysis and the approach suggested by Mami et al. (2017) to account for specific emission reduction targets relevant for the aeronautical industry (i.e. CO_2, NO_x, PM). The Environmental Life-cycle Assessment aligns with ISO (2006a, 2006b) and adopts a distance-to-target approach for the characterization, normalization and weighting phase. Costs are calculated using environmental LCC (Hunkeler et al., 2008b) on a consistent system boundary as for LCA. The marginal eco-efficiency approach of Huppes & Ishikawa (2005c) is adapted to quantify and interpret the eco-efficiency as trade-offs scenarios between the normalized costs and impact scores.

In addition to the approach proposed by Mami and colleagues (2017), an uncertainty assessment step is added to evaluate the confidence level given to the eco-efficiency results. A dependent presampled uncertainty approach is implemented using aggregated datasets. This method has proven to provide identical results to those obtained by Monte Carlo analysis using unit process datasets, with a very short computation time (Lesage et al., 2018). This novel approach has the advantage of being implementable in simplified eco-design tools. Finally, a global sensitivity analysis is performed to identify the most contributing parameters to results uncertainty (Groen et al., 2017; Saltelli et al., 1999).

4.2 Description of the case study

The aircraft part designed by the industrial partners is made from metal (Inconel 718 alloy) (Figure 4.1).



Source : P&WC

Figure 4.1: Part selected for the case study

Such metallic parts are usually either produced conventionally, i.e. material is subtracted from an initial metal stock (also called « semi-finished product »), or 3D printed, i.e. material is added by layers (Gibson et al., 2010). From an initial detailed drawing of the part, one can know its dimensions, tolerances[2] and surface roughness[3] required to meet its mechanical properties.

If this part were to be manufactured, both CM and AM processes would lead to a part with the same shape, however, the resulting surface roughness would not be the same. AM requires additional post-processing steps, such as stress relief thermal treatment (done to reach mechanical properties which could have been altered during the printing) and surface finishing. The latter is carried out to subtract machining allowances[4] by conventional technologies.

In a context where different processes are involved in the production of parts, it becomes interesting to evaluate the economic and environmental performances of different design scenarios in order to decide whether or not they align with the interests of the industry. The case study provides a real framework to test and apply our eco-design methodology in order to support an eco-efficient design of aircraft components.

---

[2] Permitted limit of variation of the dimensions in the drawing.

[3] Predicts the texture of the surface.

[4] Thickness of additional material

4.3 Methodological Framework

Figure 4.2 below describes the general framework of the eco-efficiency based eco-design methodology. Each of the steps, from the goal and scope definition, to the results interpretation, is adapted to answer the objectives set in the previous chapter. It includes the objectives, goal and scope definition, the environmental life-cycle assessment and life-cycle costing, the eco-efficiency quantification and results interpretation. The *uncertainty assessment* is integrated and happens in parallel with the LCA, LCC, eco-efficiency assessment, and must align with their objectives, goal and scope.

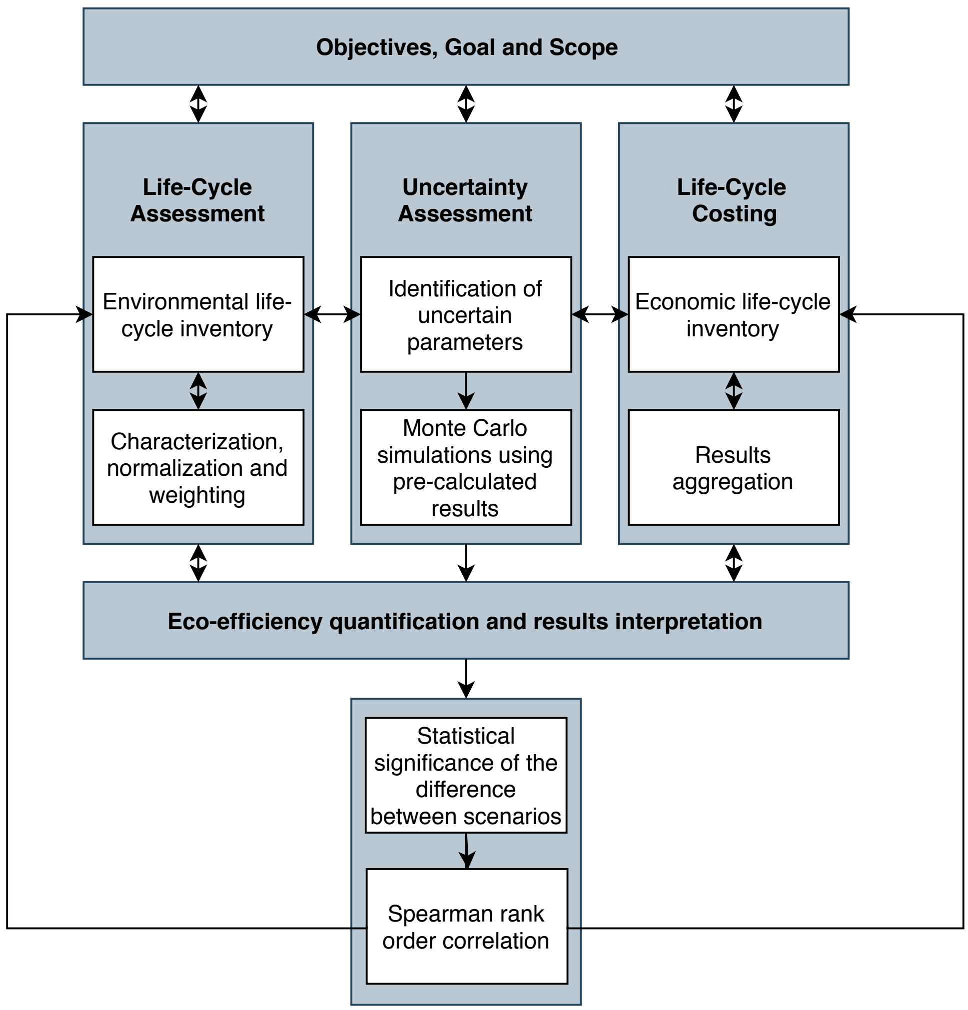


Figure 4.2: Eco-design methodology

4.4 Eco-efficiency

4.4.1 Objectives, goal and scope

The eco-efficiency assessment is applied to the life-cycle of an engine part produced by conventional and additive manufacturing technologies. Its objective is to evaluate the environmental and economic performances of the selected engine part. Then, it aims to combine both dimensions in an eco-efficiency XY diagram to evaluate the most eco-efficient manufacturing alternative. More specifically, the methodology applied to the case study, aims to:

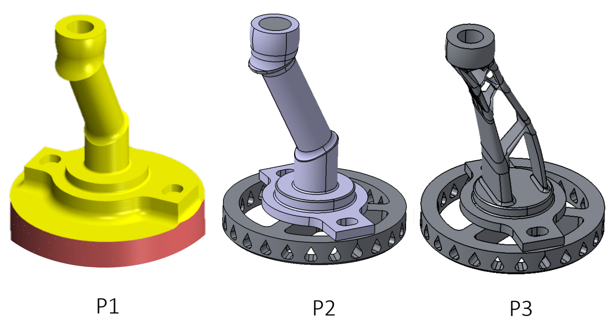
- Compare the potential life-cycle environmental impacts of an aircraft part made by additive manufacturing (AM) versus conventional manufacturing (CM)
- Compare the life-cycle cost of an aircraft part made by additive manufacturing versus conventional manufacturing
- Identify the “hot spots” in the environmental impact and cost assessments
- Combine the environmental and economic dimensions using the eco-efficiency concept developed by Mami et al. (2017), evaluate and identify the most eco-efficient scenario
- Highlight the potential of topology optimization enabled by AM in terms of environmental impact, life cycle cost, and eco-efficiency
- Understand and assess the underlying uncertainties to evaluate the confidence on the results and the conclusions. Allow a better risk management in the eco-design process.
- Compare the product systems under uncertainty and identify the most contributing parameters to the uncertainty.

4.4.2 Product systems compared

The product systems compared are the following (Figure 4.3) (the circular base is further separated from the part):

1) ***Part 1 (P1)*** is the typical CM scenario. The part is entirely machined from the cylinder stock.

2) ***Part 2 (P2)*** has the same geometry than P1 but is designed for AM, with machining allowances for the functional surfaces[5]. The part is manufactured using Laser Powder Bed Fusion Additive Manufacturing technology (LPBF-AM). After AM, the functional surfaces are machined (conventional manufacturing) and the part results in the same shape and mass as P1.
3) ***Part 3 (P3)*** is designed for AM, but has an optimized topology[6], which enables a weight reduction; this part is manufactured using LPBF-AM with machining allowances for the functional surfaces; after AM, the functional surfaces are machined.



Source: P&WC

Figure 4.3: Design scenarios of the selected part

P1 is made from Inconel 718 stock, whereas P2 and P3 are made from IN718 powder. At the end of the production stage, P1 and P2 have the same geometry and weight 90 g each, whereas P3 is lighter (77 g) and highlights the technological benefits of AM (i.e. around 15% weight reduction). One must note the major differences between the three parts: going from P1 to P2, the manufacturing technology changes. Going from P2 to P3, the technology is the same however, the geometry changes.

P1 is considered as the reference or base scenario to which P2 and P3 are compared.

---

[5] Surfaces of contact between two components

[6] The material distribution is optimized within the design space, thus reducing the quantities of powder required to produce the part by additive manufacturing. Topology optimization was realized by Pratt & Whitney Canada.

The framework is representative of the Quebec, Canada context in 2018. The assessment is considered as starting at the tests and prototype step in the eco-design process (refer to section 2.2.1 in the literature review), i.e. after the planning, conceptual design and detailed design stages. This means that the research and development are excluded, because they have already taken place and they are no longer part of the decision-making process: their associated environmental impacts (although negligible) and costs do not affect the overall eco-efficiency of the compared product systems.

All the actors in the life-cycle process are considered, even thought they might not be part of the decision-making process (example: end-of-life is not directly managed by any of our industrial partners, but it is still taken into consideration in the assessment).

4.4.3 Function and functional unit

Although P1, P2 and P3 result from different designs and manufacturing processes, the parts fulfil the same function which is “ensuring the assembly of other components in an aircraft’s turbine engine”. It is limited to the part relatively to an aircraft. Therefore, the lifetime of an aircraft is used to quantify the function: the functional unit is “ensuring the assembly of other components in an aircraft engine during the aircraft lifetime" (90 000 hours of operation, (Bombardier, 2016)).

4.4.4 System boundaries of the product system.

The product systems are compared from cradle-to-grave. Thus, the assessment includes all stages from the extraction of raw material used to produce the part to its end-of-life (Table 4.1).

The boundaries are equivalent for LCA and LCC. However, they differ depending on their significance relatively to the environmental and economic dimensions respectively. For example, while labour is negligible in LCA (not included), its associated costs are significant in LCC and cannot be excluded. Finally, the processes which are identical for the compared products are excluded. Only those differing from a scenario to another are taken into account.

Description of product systems

The detailed description of the products systems for parts P2 and P3 (AM) and for part P1 (CM) is provided in Appendix A . The AM life-cycle starts with the *pre-production* phase. It considers commodity production, i.e. all material needed for the production of parts: metal powder, metal platform, autocad file and argon. For CM, the production of a metal cylinder is used instead.

Following is the *production* phase during which the part is 3D printed using a laser sintering system EOSINT M280. The latter follows regular maintenance (its filters are replaced and internal compartment is cleaned with vacuum cleaner). Then, once the part is printed, it undergoes post-processing (stress relief heat treatments in an industrial electric oven under argon protective atmosphere). The platform and supports are removed and the platform rectified. Finally, the part surface is finished. The printing process generates waste which is included in the assessment (collected from the process, in the filters and by a vacuum cleaner). For CM, the metal cylinder is introduced in a 5-axes machining center: material is subtracted, generating waste which is also included in the assessment. After that, the part can also undergo additional surface finishing.

Afterwards, the parts are shipped to the factory where the aircraft is *assembled*. This stage is excluded from the study because it is considered to be the same for all scenarios.

The *use phase* is limited to the fuel consumption during aircraft operation. The aircraft maintenance activities are also excluded from the study because they are considered to be the same for all scenarios.

The *end-of-life or waste management* considers different types of waste and waste management options. First, the waste from parts: these are either landfilled or recycled when they reach their lifetime. Then there is the waste from the metal powder or metal cylinder lost during the AM or CM processes. The metal powder collected from the filters or the vacuum cleaner is considered as hazardous and treated as such (conditioned and stored underground). The metal powder lost in support in AM, the metal lost from the metal cylinder in CM, and the waste from the platform, may either be landfilled or recycled. Here, landfilling is considered as the default scenario. As for the waste management, when landfilling is considered, the waste is modeled as inert material. For recycling, ecoinvent processes are chosen to represent the recycling activity and the avoided products (if credit is given for avoiding virgin material production).

Table 4.1: Included/excluded processes for eco-efficiency

Life-cycle stage	Case study	LCA	LCC	Comments
Research & Development	Labor & tests	Excluded	Excluded	It is considered as already carried out and does not affect decision making
Pre-production	Extraction of raw material and production of all other materials needed for the production of the parts	Included	Included, accounted for in the purchase price of the material	Material and alloy production (metal powder for P2 and P3, metal stock for P1) Infrastructures are not included because of the lack of data
	Transport to semi-finished product site and production of semi-finished products	Included		
	Transport of semi-finished products to production site	Included		
Production	Infrastructures	Included	Included	3D printer, CM machine (and their maintenance) are included but the infrastructures hosting them are not
	Production equipment	Included	Included	Fluids, equipment and tooling for machines, electricity, etc.

Table 4.1: Included/excluded processes for eco-efficiency (Continued)

Life-cycle stage	**Case study**	**LCA**	**LCC**	**Comments**
	Post-processing	Included	Included	Post-AM stress relief thermal treatment and machining of AM parts are included
	Transport from production to assembly site	Included	Included	
Assembly	Infrastructures	Excluded	Excluded	Not relevant for the comparative assessment
	Aircraft production	Excluded	Excluded	It is the installation of the part into the aircraft. It is not relevant for the comparative assessment.
Use	Acquisition of spare parts	Included	Included	Already accounted for in the pre-production and production stages
	Storage and insurance of spare parts	Excluded, because considered negligible	Included	
	Aircraft operation	Included	Included	Included, limited to aircraft fuel consumption

Table 4.1: Included/excluded processes for eco-efficiency (Continued and end)

Life-cycle stage	Case study	LCA	LCC	Comments
	Aircraft maintenance	Excluded	Excluded	Not relevant for the comparative assessment
End-of-life	Transport from disassembly site to treatment site (landfill or recycling)	Included	Included	
	Product recycling or landfilling	Included	Included	Waste management of Powder/metal stock lost during the production phase, build plate end-of-life, initial part installed and spare parts end-of-life
	Avoided production	Included or excluded	Included or excluded	100% credit rate given for avoided production of virgin material. This rate is applied to prevent double counting of the recycling benefits between the recycled material provider and user
	Resale gain of recycled material	Not relevant for LCA	Included or excluded	Applied if boundaries are extended in LCA

4.4.5 Allocations to external systems

The potential environmental impacts and costs associated with each life-cycle stage must have their responsibility assigned to processes which are multifunctional. Machines and equipment are allocated to the studied part. There are two options for allocating the kerosene consumption (for calculations, refer to section 4.4.6):

i) the kerosene consumption allocated to the part is calculated as a fraction proportionally to the kerosene consumed by the aircraft. This means that, if the aircraft mass is increased, the fuel consumption will increase proportionally. Thus, the kerosene consumption is evaluated based on the total fuel consumed by the aircraft, its weight and the weight of the part,

ii) the kerosene consumption is calculated as a function of the marginal change in weight compared to an existing baseline (the current aircraft). This means that if the aircraft mass is increased, the fuel consumption will increase marginally.

At the end-of-life, waste materials can be recycled into new materials. Even though this is true, the recycling process is excluded from the system boundaries because the recycling of nickel alloys is considered to be difficult (Corrotherm, 2018). Therefore, the part is assumed having zero value for recycling and zero economic value; it is considered as completely landfilled. Nevertheless, for the purpose of sensitivity analyses, recycling processes and credit for recycled materials avoiding virgin material production are included.

4.4.6 Life cycle environmental and economic inventory

The life-cycle inventory is built on the data collection related to all the processes included in the system boundaries. In other words, materials, energy consumption, waste and emissions generated for AM and CM processes respectively are considered.

This project relies on the life cycle assessment model developed at CIRAIG (2018) in the context of the Manu-710 project. It provides a comparative assessment of the potential environmental impacts of parts P1, P2 and P3 along their life-cycle. The extractions and emissions from and to the environment are translated into impacts on human health, climate change, ecosystems quality and resource consumption. Data collection (building of product systems) was supported by members[7] of the CRIAQ (Consortium de recherche et d'innovation en aérospatiale du Québec) involved in this project.

Additional practical data was generated (e.g. manufacturing time, parts volumes, quantities of metal powder or cylinder - Appendix B) and was used by the LCA and LCC models. This was done through numerical simulations of the manufacturing processes resulting in parts P1, P2 and P3. They were performed by Victor Urlea[8] and Olivier Boudreau-Rousseau[9] (LAMSI). These simulations were carried out for different batch sizes (1, 9 and 90 parts). A sensitivity analysis is done further to show the influence of the batch size on the environmental impacts and production costs.

Model hypotheses

To compute the emissions associated to the parts during the use phase, the following parameters are determined:

a. Number of parts (as seen in the function and functional unit section, 7 parts are required to fulfill the functional unit)

The parts, once installed in the aircraft, wear and must be replaced. Their average lifetime is estimated around 15 000 hours. Thus, in addition to the original part installed, 6 replacement or spare parts are needed for maintenance. Consequently, all inputs and outputs are normalized to the total number of parts over the aircraft lifetime (equation 7).

$$N_t = N_{ip} + N_{sp} \tag{7}$$

With:

---

[7] Laboratoire sur les alliages à mémoire et systèmes intelligents (LAMSI) (École de Technologie Supérieure, ETS), CRIQ (Centre de Recherche Industrielle du Québec), Fusia, Pratt & Whitney Canada, and Bell Helicopter.

[8] Simulation of AM parts (P2, P3). Procedure illustrated in Appendix B

[9] Simulation of CM part (P1). Procedure illustrated in Appendix B

N_t: Total number of parts over aircraft lifetime

N_{ip}: Number of initial parts installed

N_{sp}: Number of spare parts used for maintenance

The value of N_{ip} is set to one. Furthermore, the part volume was identified as a key parameter for the reference flows because it has an important influence on reference flows and life-cycle impacts of parts (CIRAIG, 2018; industrial partners). Consequently, it must be carefully evaluated to compare the manufacturing scenarios, because of its important influence on the life cycle impacts and costs.

b. Airplane traveled distance*:* the average airplane speed (829 km/h) is used to compute the traveled distance of airplanes during their lifetime. Thus, the airplane traveled distance over its whole life cycle is 74 610 000 km.

c. Aircraft kerosene consumption*:*

Dandres (CIRAIG, 2018) calculated the marginal kerosene consumption factor for a marginal increase of weight being 4×10^{-5} kg-fuel/km/kg (CIRAIG, 2018). To do so, he used the fuel consumption data as a function of the number of passengers using the airplane transport process of ecoinvent v3.3 "*Transport, freight, aircraft (RoW)| intracontinental*", the Bombardier EPD use case for airplanes (Bombardier, 2016; Oudjehani, 2015) and the technical sheets of Bell Helicopter models found on the company website.

For example, if P3 (AM optimized) is compared to the reference scenario P1 (CM), the fuel consumption due to the weight of part P1 is first calculated (equation 8):

$$F_{P1} = m_{P1} \times F_{\frac{kg\ fuel}{km.kg}} \times d \tag{8}$$

Then the fuel consumption for P3 is calculated using the differential consumption (equation 9):

$$F_{P3} = F_{P1} - (m_{P1} - m_{P3)} \times F_{differential} \times d \tag{9}$$

Where:

F_{P1} : Fuel consumption for P1

m_{P1}: Mass of P1

$F_{\frac{kg\,fuel}{km.kg}}$: Fuel consumption per km.kg (4×10^{-4} kg-fuel/km/kg)

d : Traveled distance

$F_{differential}$: Differential fuel consumption due to airplane weight increase by 1 kg (4×10^{-5} kg-fuel/km/kg)

Since P2 and P1 have equal masses, their associated fuel consumption is the same.

The following table shows the major hypotheses made for the production cost model.

Table 4.2: List of major hypotheses for the production cost model (source: LAMSI)

General hypothesis	
i.	The cost of P2 and P3 amounts to the sum of their AM and post-AM machining operations costs.
ii.	The cost of P1 amounts to the machining cost of the part from the metal cylinder.
Hypotheses established for the AM simulations	
i.	The cost of each AM part is first calculated for the AM processing only (as-built part) and then, for the combined AM and post-AM machining.
ii.	The cost to produce one as-built component takes into consideration the costs of powder feedstock, electricity and protective gas supplies, machine exploitation and maintenance, labor (programming, setup, monitoring), processing time, and the number of parts per plate.
iii.	The volume of powder lost during AM in the filters and vacuum cleaner represents 20% of the sum of the part and supports volumes.
Hypotheses established for the CM simulations	
i.	The cost of machining of a given number of parts "n" greater than 1 corresponds to the sum of the costs of the first part and the (n-1) parts in production.
ii.	The cost of machining takes into consideration the labor costs (programming, setup, monitoring), machine exploitation and maintenance costs, coolant and tooling (mounting template) supplies, machining time, and the batch size.

Table 4.2: List of major hypotheses for the production cost model (source: LAMSI) (Continued and end)

iii.	Time invested in programming machining operations is almost 4 times longer than that invested in programming AM processing.
iv.	Time invested to machine a first part is almost 4 to 5 times longer than that to machine subsequent parts (these are produced in volume, once the production is stabilized).

4.4.7 Life-Cycle Assessment

ISO 14045 (2012) on eco-efficiency recommends that the LCA be aligned with ISO 14040 (2006a) and ISO 14044 (2006b) to assess the environmental dimension of the eco-efficiency framework. This study relies on the LCA model and results of Dandres (CIRAIG, 2018) providing the environmental profile for each of the scenarios considered in our case study. The life cycle inventory relies on the ecoinvent v3.3 database. The impact scores are characterized here through the ReCiPe 2008 (Goedkoop et al., 2009) and IPCC 2013 (Stocker et al., 2013) methods. ReCiPe 2008 includes 18 midpoint categories and 3 endpoint categories (damage to human health, ecosystems quality, resources). In this method, the impacts of climate change at the midpoint level contribute to the damages on human health and ecosystems quality. Therefore, its contribution to these two endpoints is subtracted and IPCC 2013 is directly used to present climate change results. Climate change results are chosen to be presented separately because: i) they are easier to understand when expressed in terms of "CO_2 eq" rather than "DALY" or "species.yr", ii) they are used further in the distance-to-target approach (explained in the paragraph below).

For the case study, the results obtained through ReCiPe 2008 and IPCC 2013 are first presented and a contribution analysis by midpoint impact category is performed. Additionally, to meet the aeronautical industry interests, the distance-to-target weighting approach elaborated by Mami et al. (2017) is applied. It specifically addresses criteria pollutants and reduction goals set by the aeronautical industry for the carbon dioxide (CO_2), nitrogen oxides (NO_x) and particulate matter (PM) use phase emissions compared to 2005 levels: 50% CO_2 reduction by 2020 and 75% by 2050; 80% NO_x reduction by 2020 and 90% by 2050; 65% PM reduction by 2050 (IATA, 2013). However, the model of Dandres (CIRAIG, 2018) does not provide the life cycle inventory of emissions. Therefore, IPCC 2013 (Stocker et al., 2013) is used to represent the CO_2 emissions, and ReCiPe 2008 (Goedkoop et al., 2009) for the NO_x and PM emissions. In fact, the ReCiPe midpoints are used to calculate the NO_x emissions[10], dividing each midpoint impact score by the NO_x emission corresponding characterization factor. The particulate matter formation midpoint is used to represent the PM emissions.

The calculations are translated by equations 10,11,12 and 13 (Mami et al., 2017). The distance-to-target approach includes a weighting factor which accounts for the distance between a current state (current emissions of an aircraft) and a target state (target emissions of an aircraft). Also, the time left to reach targets is considered, i.e. more or less importance is given to emissions which must be reduced in a shorter time. Finally, an ecological factor is added to set the equivalency of damages at the aircraft target levels.

In equation 10, the emissions are first characterized per impact category, using the characterization factor of the selected impact assessment method, then normalized by the corresponding impact category score of the aircraft life-cycle. Finally, they are aggregated into a single score using the weighting factor $\frac{w_c}{\sum_{c=1}^{k} w_c}$.

w_c is the product of factors (a), (b) and (c) in equation 11 (all three factors and normalized to 1, i.e. the ratio is comprised between 0 and 1). (a) is the distance to target factor, it links the current aircraft emissions to the target aircraft emissions. The impact category with the highest factor is given a stronger weight, i.e. the gap between the current and target state is the greatest, and a higher importance is given to the seriousness of that impact category. (b) is the time to target factor: the impact category with the highest factor is given a stronger weight, i.e. the time to reach the targets for that impact category is the shortest. (c) is the damage equivalency at target level factor which is included to "make corrections in the case that the distance-to-target approach does not sufficiently represent the seriousness" (Goedkoop & Spriensma, 1995) of damages at target levels (similar to experts panel).

---

[10] The assumption on which relies this calculation might overestimate the real value of the NO_x emissions.

$$I_i = \sum_c \sum_j \frac{e_{ij} \times f_{jc}}{I_c} \times \frac{w_c}{\sum_{c=1}^{k} w_c} \tag{10}$$

$$w_c = \overset{(a)}{\boxed{\frac{\frac{I_c}{T_c}}{\sum_c \frac{I_c}{T_c}}}} \times \overset{(b)}{\boxed{\frac{\bar{Y}_c}{\sum_c \bar{Y}_c}}} \times \overset{(c)}{\boxed{\frac{D_c}{\sum_c D_c}}} \tag{11}$$

$$I_c = \sum_j E_j \times f_{jc} \tag{12}$$

$$T_c = \sum_j T_j \times f_{jc} \tag{13}$$

Where:

I_i: Aggregated environmental impacts score for the assessed scenario i

e_{ij}: Emissions of inventory substance j for the assessed scenario i

f_{jc}: Characterization factor of inventory substance j to impact category c

w_c: Weighting factor of impact category c

I_c: Impact score of the aircraft life cycle for impact category c

E_j: Current emissions of the aircraft life cycle for inventory substance j

T_c: Aggregated target emissions of the aircraft life cycle for impact category c

T_j: Target emissions of the aircraft life cycle for inventory substance j

$\bar{Y}_c$: Mean of the reverse of the years left to reach target reductions of impact category c

D_c: Damage at target value for impact category c

The normalization reference is defined as the life-cycle impacts of an aircraft meeting the target values. Therefore, an alternative scenario compared to the base scenario would contribute to improving or deteriorating x% of the environmental impacts of an aircraft. This normalization step is done because the impact of the studied component itself is not so relevant but rather the degree to which the impact contributes to the total problem (the impacts of an aircraft) (Goedkoop & Spriensma, 1995).

As the use phase (kerosene combustion) represents more than 95% of the aircraft environmental impacts (CIRAIG, 2018), the aircraft fuel consumption is used as a reference process to generate the corresponding life cycle emissions. The damage equivalency at target level is set to 1, meaning that equal weighting is given to damages at target levels (mutually comparable reduction objectives and target values can be formulated only if all damage levels are equal, Goedkoop & Spriensma (1995)).

A sensitivity analysis to the distance-to-target approach is done by ranking the manufacturing scenarios of the case study by endpoints (ReCiPe 2008) and by emission score, i.e. the amounts of CO_2, NO_x and PM (Mami et al., 2017). A comparison can be made to show whether the obtained ranking is the same when the indicator is changed.

Additionally, the part lifetime in an aircraft is of 15000 hours. Spare parts are needed to replace the original one at the end of its lifetime. Consequently, it is interesting to evaluate the impacts and costs of a batch production (more than 1 part can be produced). Hence, a sensitivity analysis for batch sizes of one and 9 parts is performed (i.e. one part is placed alone on the build plate and 9 parts are placed in a batch on the same build plate for AM, Figure 4.4).

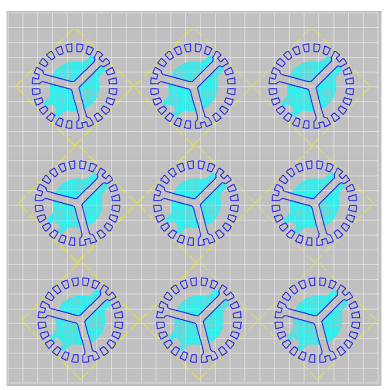


Figure 4.4: 9 parts placed on the build plate for AM (seen from above)

4.4.8 Environmental Life-cycle costing

The Environmental Life-Cycle Costing (Hunkeler et al., 2008a) is used to evaluate the economic performance of parts P1, P2 and P3. This method aligns with the goal and scope of the eco-efficiency framework. The system function stays the same. Costs are quantified to meet the same functional unit as in the LCA.

The company costs (or market prices when data is not available) are used rather than the value or profit. Although usually included in life-cycle costing, the research and development costs are not calculated because they are considered as past costs (Kuosmanen, 2005) (the eco-efficiency assessment happens in this study after the R&D phase, and the scenarios have already been designed). They are thus, not relevant anymore for the decision-making process. Pre-production is not included because there was not enough information on the cost of upstream processes. Accordingly, the price of material is taken as an aggregated data. During the production phase, we take into consideration: the price of raw material and energy, the machine cost, the maintenance cost for the machine and equipment, the labour cost, the post-processing cost, and finally the cost of transport from the manufacturing facility to the assembly site. Post-processing is very rarely considered in cost and environmental studies but its contribution to overall costs is estimated to be the 3rd largest after the machine and materials costs (Lindemann et al., 2012). Therefore, it is considered here. The production cost is based on the calculations developed by Timercan (2017). They are updated and completed to consider the complete life-cycle of parts usually printed in the laboratory (LAMSI). The assembly phase is not relevant for the comparative assessment and is therefore not considered. The use phase accounts for the cost of fuel (2.75 CAD/gal[11]) consumed throughout the aircraft lifetime. The waste management cost is based on the cost of landfilling or recycling. Due to lack of data, this cost is considered the same.

The present value of all costs is calculated at the reference year, 2018, accounting for the inflation and discount rate, set to 3% and 9% respectively. A sensitivity analysis is performed to evaluate the influence of discounting on the life-cycle cost (discount rates of 0% and 15%, (Willcox, 2004)). The choice of a discount rate is done to evaluate a society cost. A discount rate of 0% indicates that time does not influence the value of money (the value of a dollar tomorrow is equal to that of a dollar today); accordingly, the equivalency between the LCA and LCC is strengthened because the temporal boundaries are the same (the LCA carried out here is static).

---

[11] https://www.iata.org/publications/economics/fuel-monitor/Pages/index.aspx

In order to consider discounting, the costs are first evaluated on a yearly basis. A timeline is set, starting from the reference year, which is the year where the LCC assessment initiates, until the lifetime end period of the system (here, the aircraft lifetime).

The annual cost increases each year with inflation (equation 14):

$$C_{year\ j} = C_{year\ i} \times (1 + r)^{j-i} \tag{14}$$

With:

$C_{year\ i}$: Cost at year i (reference year)

$C_{year\ j}$: Cost at year j (must be greater than year i)

r: inflation rate

Then, the annual cost is discounted as following (equation 15):

$$PC_{year\ i} = \frac{FC_{year\ j}}{(1 + d)^{j-i}} \tag{15}$$

With:

$PC_{year\ i}$: Present cost at year I (reference year)

FC_j : Future cost at year j (must be greater than i)

d : Discount rate

At this point, all the costs over the complete life-cycle of the product are future costs expressed as the corresponding amount to pay today. They can be summed up into the total life-cycle cost. Finally, the latter is normalized with reference to the life-cycle cost of an aircraft as per equation 16. Therefore, an alternative scenario compared to the base scenario would contribute to reduce or increase x% of the life-cycle cost of an aircraft.

$$LCC_{normalized} = \frac{LCC_{part}}{LCC_{reference}} \tag{16}$$

The price of the aircraft is considered to be equal to 25% of the life-cycle cost, and is therefore extrapolated in order to be used as the normalization reference (Glade, 2005; Haggerty, 2004; Mami et al., 2017; Défense nationale, 2014).

Additionally, since the part lifetime in an aircraft is of 15000 hours, and that spare parts are needed to replace the original one once it wears, the analysis of four production cases for AM is suggested to show their influence on the life-cycle cost (refer to Figure 4.4):

a) Spare parts are produced on-demand, batch 1, i.e. for AM, each part is printed alone on the build plate; for CM, one part is made from a metal cylinder.

b) Spare parts are produced on-demand, batch 9, i.e. for AM, each part is printed along with other components (for other applications) in the same batch (on the same build plate); for CM, 9 parts, each made from a metal cylinder, are manufactured in series.

c) Spare parts are produced at first, batch 1, i.e. for AM, each part is printed alone on the build plate; for CM, one part is made from a metal cylinder.

d) Spare parts are produced at first, batch 9, i.e. for AM, each part is printed along with the others in the same batch (on the same build plate); for CM, one part is made from a metal cylinder and is part of a batch (9 parts manufactured in series).

4.4.9 Eco-efficiency representation and interpretation

The distance-to-target LCA elaborated beforehand generates a normalized impact score. The environmental LCC generates a normalized cost. It is possible to place this data on an eco-efficiency graph, since both dimensions are expressed in percentage of increase or decrease of the aircraft life-cycle cost/impact. The representation in a XY diagram allows the identification of possible compromises to be made between both dimensions. The X-axis is defined as an environmental improvement, or the difference between the normalized environmental impact of the reference scenario with that of an alternative. The Y-axis is defined as a cost reduction, or the difference between the normalized cost of the reference scenario and that of an alternative.

The eco-efficiency indicator is calculated as per equation 17:

$$EE_i = C_i \times T + I_i \tag{17}$$

Where:

EE_i: Eco-efficiency indicator for the assessed scenario i

C_i: Aggregated cost for the assessed scenario i (normalized)

T: Cost-to-environment trade-off factor, defined as a subjective value expressing the importance of the cost relatively to the environment.

I_i: Aggregated environmental impacts score for the assessed scenario I (normalized).

The highest eco-efficiency indicator represents the most eco-efficient alternative.

4.5 Uncertainty Assessment

The uncertainty assessment aims first to inform on the degree of certainty of conclusions (uncertainty analysis). On another hand, it aims to identify the key parameters having the greatest influence on the results uncertainty (sensitivity analysis). The general approach is summarized in Figure 4.5 (adapted from Saltelli et al. (1999), Groen et al. (2017)).

Only parameter uncertainty is evaluated (scenario and model uncertainty are not considered). The approach is based on a stochastic analysis of the life-cycle impacts, costs and eco-efficiency of scenarios P1, P2 and P3.

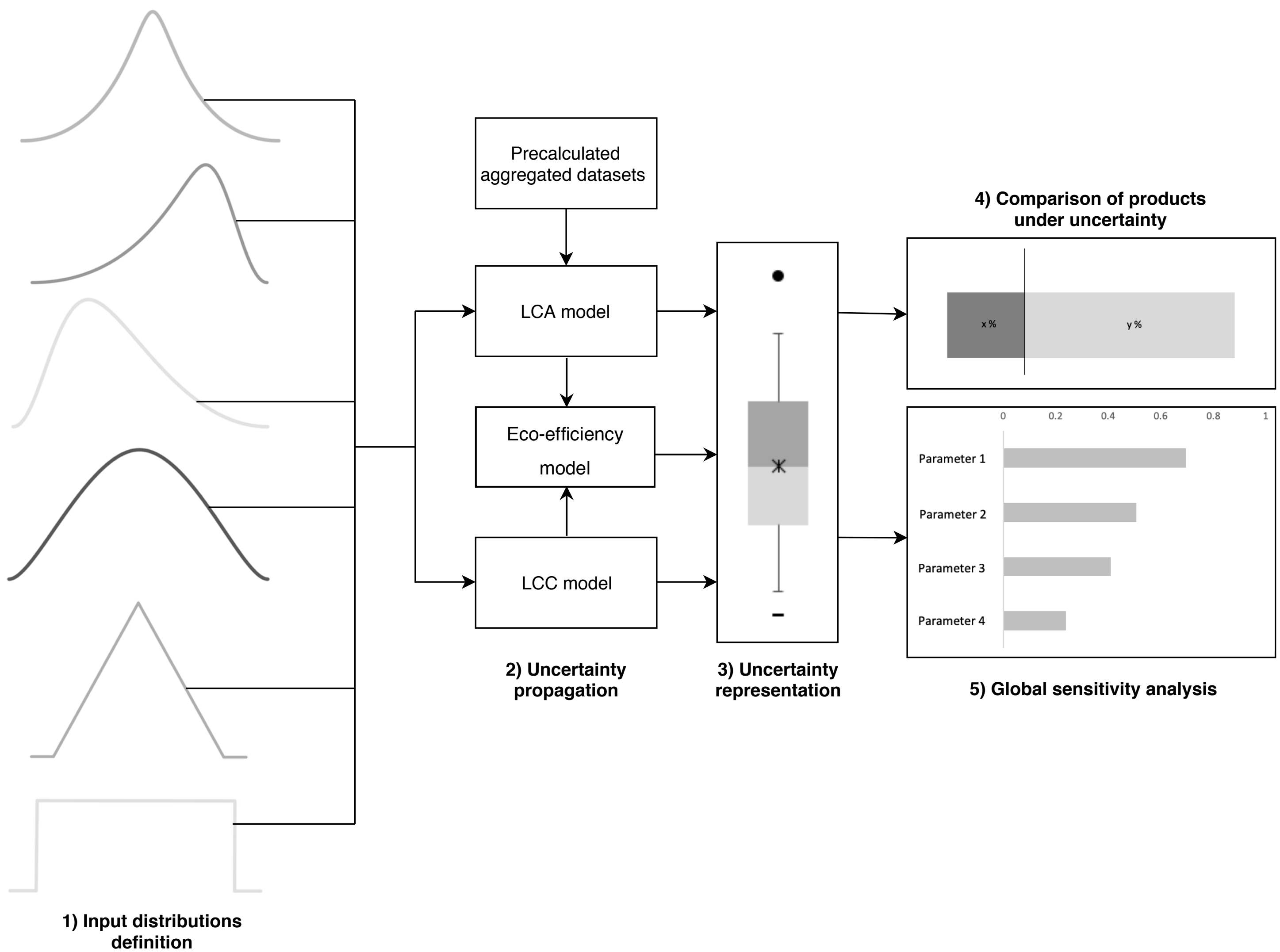


Figure 4.5: Uncertainty assessment (adapted from Saltelli et al. (1999), Groen et al. (2017))

4.5.1 Uncertainty analysis for Life-Cycle Assessment

The uncertainty analysis for LCA is based on the use of presampled aggregated datasets (Lesage et al., 2018). These precalculated iterations are generated for a specific number of final demands (i.e. number of products in the LCA model for which aggregated datasets are required) by calculating the LCIA score using the selected LCIA method (ReCiPe 2008 and IPCC 2013). They are then stored as background data in order to be used in Monte Carlo simulations (this procedure is illustrated in Appendix C). These precalculated results only account for LCI uncertainty; the uncertainty of impact assessment method is not considered (although it is inherent to characterization and normalization factors).

The LCIA result array is expressed by (equation 18):

$$LCIA\ Result\ array = \left[\left(\sum_{j=1}^{m} a_j x_j\right)_1, \left(\sum_{j=1}^{m} a_j x_j\right)_2, \dots, \left(\sum_{j=1}^{m} a_j x_j\right)_n\right] \quad (18)$$

Where:

n: Number of Monte Carlo iterations

m : Number of aggregated datasets used in the system

a : Scaling factor

x : Aggregated result for dataset j

The scaling factor is generated n times using random sampling from the probability density functions attributed to each uncertain input parameter (foreground data). The uniform distribution is used as a rough estimation of the variability of input parameters (an equal probability is given to minimum and maximum values) (step 1, Figure 4.5).

This method is applied to each of the case study scenarios, making sure that the iterations for common scenario parameters are the same. The uncertainty is propagated through the LCA model (step 2, Figure 4.5). Then, the LCA results are presented as in step 3 of Figure 4.5.

Afterwards, the probability of a scenario being better than another is calculated (step 4, Figure 4.5). In other words, the scenarios are compared under uncertainty, by counting the share of Monte Carlo iterations where one scenario has a lower/higher LCIA score than another scenario.

4.5.2 Uncertainty analysis for Life-Cycle Costing

LCA and LCC require different calculation steps. While a set of ordered arrays generated from the ecoinvent v.3 cut-off database are used in LCA uncertainty analysis, only probabilistic input data on cost and input parameters is needed for the LCC uncertainty analysis. Random values are first sampled for input parameters based on their attributed probability density function (step 1, Figure 4.5). The uniform distribution is used. Then, the uncertainty is propagated through the LCC model (step 2, Figure 4.5): for each iteration n, the life-cycle cost is calculated by using the corresponding probabilistic parameters values. Afterwards, the uncertainty is represented (step 3, Figure 4.5). Finally, the scenarios are compared under uncertainty by calculating the probability of a scenario being better than another (as done in the LCA uncertainty analysis) (step 4, Figure 4.5).

4.5.3 Uncertainty analysis for eco-efficiency

Probabilistic data on the eco-efficiency input parameters is needed for the eco-efficiency uncertainty analysis. Random values are sampled for these parameters based on their attributed probability density function (for example, the normalization references) (step 1, Figure 4.5). The uniform distribution is used. Then, the uncertainty is propagated through the eco-efficiency model, using dependent sampling of the distance-to-target LCA and LCC uncertainty results (step 2, Figure 4.5): for each iteration n, the eco-efficiency indicator is calculated using equation 17 (refer to section 4.4.9). If the trade-off is considered to be stochastic (it is not always equal to one), it is given random values which are sampled based on a uniform distribution. The scenarios are compared under uncertainty by calculating the probability of a scenario being better than another (step 4, Figure 4.5). For the eco-efficiency uncertainty representation, the thousand Monte Carlo (x,y) coordinates (environmental improvement and cost reduction uncertain results) are located on the eco-efficiency diagram.

4.5.4 Global sensitivity analyses for Life-Cycle Assessment, Life-Cycle Costing and eco-efficiency

A global sensitivity analysis is performed to determine the contribution of each input parameter to the results uncertainty. As a consequence, this step supports information gathering and data collection. Thus, it would help improve and refine the environmental impact and cost results, by decreasing the parameter value uncertainty.

The analysis is carried out using the Spearman rank order coefficient (equation 19).

$$\rho(X,Y) = 1 - \frac{6 \times \sum_{i=1}^{N}(r(X_i) - r(Y_i))^2}{N^3 - N} \tag{19}$$

Where:

ρ (X,Y): Spearman coefficient for the correlation of parameters X and Y

$r(X_i)$: rank of i^{th} value of X in the distribution $X_1 \ldots X_N$

$r(Y_i)$: rank of i^{th} value of Y in the distribution $Y_1 \ldots Y_N$

N: Number of samples in the distribution

In other words, for each input parameter, the 1000 corresponding Monte Carlo values are ranked. Also, for the life-cycle impact, the 1000 corresponding values are ranked. Then, the Spearman rank order coefficient for the correlation between each input parameter and the life-cycle impact is calculated. The latter is also done for the correlation between the input parameters and the life-cycle cost and ultimately the eco-efficiency.

Finally, the Spearman rank order coefficient for each of the input parameters is plotted in a horizontal column bars chart (step 5, Figure 4.5). This representation helps identifying the parameters contributing the most to the results uncertainty.

4.5.5 Local sensitivity analyses

Local sensitivity analyses are performed in order to evaluate how a variation in one input parameter at a time influences the outcome (LCA, LCC or eco-efficiency results) (Table 4.3).

Table 4.3: Local sensitivity analyses performed

Parameter	LCA	LCC	Production cost	EE
Standard / distance-to-target LCA	x			
Batch size	x	x	x	x
Production scenario (initial or on-demand)		x		
Discount rate		x		
Recycling and credit to recycling	x	x		
Fuel consumption modelling	x	x		

CHAPTER 5 RESULTS AND DISCUSSION

This chapter presents at first the results of the life-cycle assessment and the life cycle costing. Then, the eco-efficiency is represented in an XY diagram. Afterwards, the uncertainty and sensitivity analyses results are described. Finally, the strengths, limits and outcomes of the case study results are discussed, followed by a general discussion on the stochastic eco-efficiency methodology. As a reminder of the case study, P1 is the conventional manufacturing scenario (CM). The part is completely machined from a metal cylinder. P2 has the same geometry as P1 but is additively manufactured (AM). P3 is additively manufactured with topology optimization (AM Optimized). P1 and P2 have the same mass whereas P3 is 15% lighter.

5.1 Life-Cycle Assessment

This section presents the results of the LCA, assuming parts are produced in a batch of 9.

5.1.1 Environmental profile at damage level (ReCiPe 2008, IPCC 2013)

The environmental profile of the three parts is presented in Figure 5.1 in terms of impacts on human health, ecosystems quality and resources consumption using ReCiPe 2008 (Goedkoop et al., 2009). The contribution of climate change to human health and ecosystems quality is subtracted and IPCC 2013 (Stocker et al., 2013) is used instead to represent the impacts on climate change.

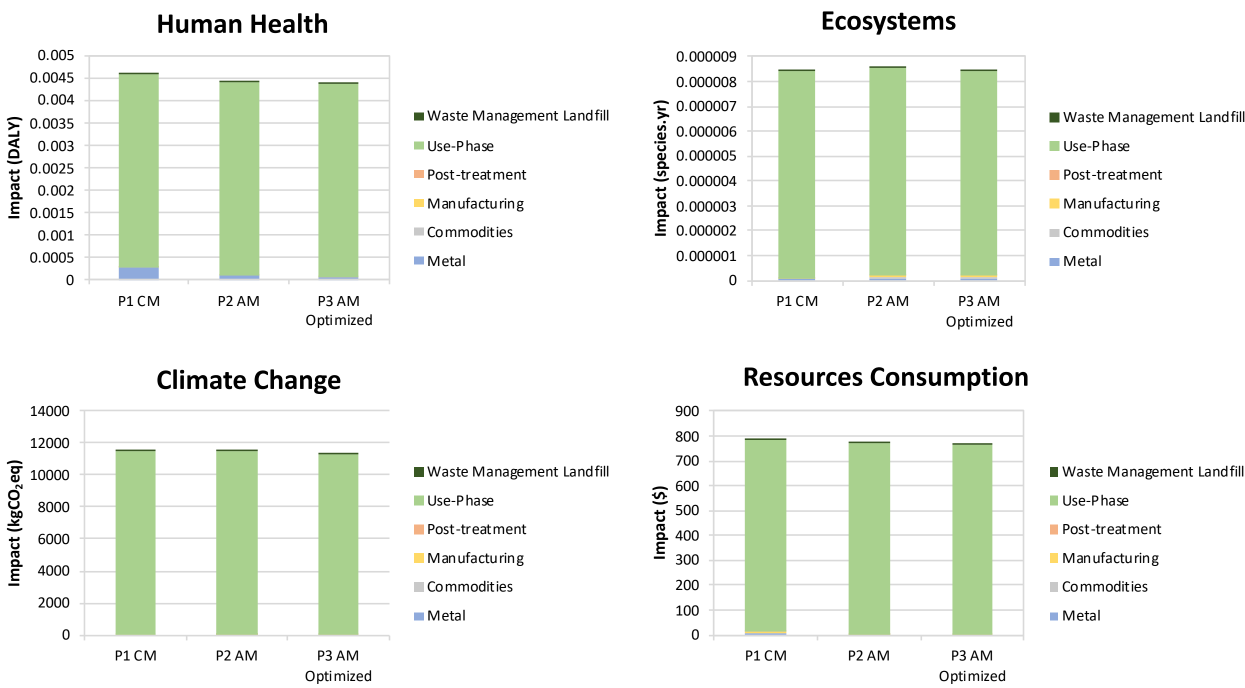


Figure 5.1: Environmental profile of P1 (CM), P2 (AM) and P3 (AM Optimized) in terms of human health, ecosystems quality, climate change and resources consumption

Figure 5.1 shows that the use phase contributes to more than 95% of the environmental impacts on either of the four environmental indicators. This is due to the kerosene combustion during aircraft operation, and is true for all three manufacturing scenarios P1, P2 and P3. Nevertheless, the comparison between the parts is difficult when looking at absolute results, because the use phase impacts are dominant and do not allow us to compare the other life-cycle stages.

Therefore, Figure 5.2 presents the relative change in the environmental impacts of P2 and P3 relatively to P1. The reduction or increase percentage in terms of the four previous indicators is observed. A negative percentage shows an environmental improvement.

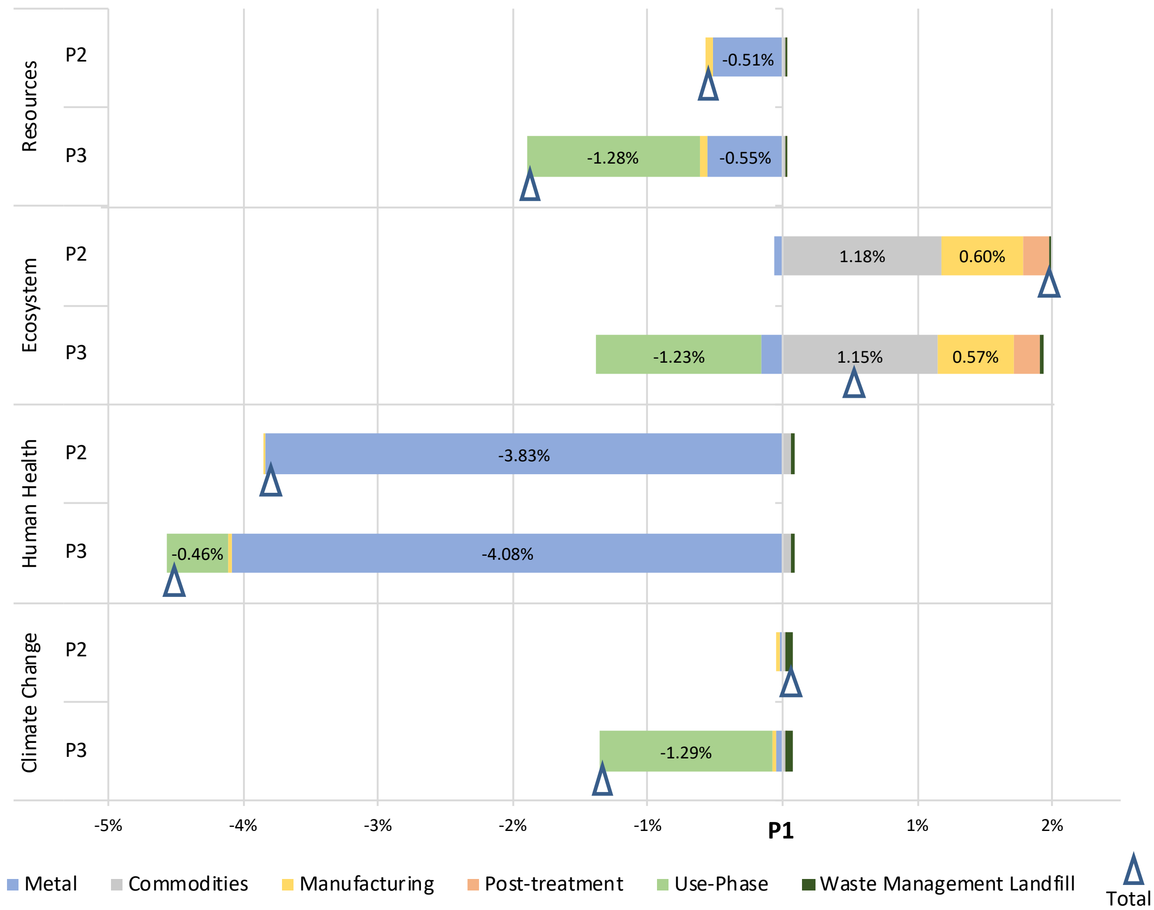


Figure 5.2: Environmental profile of P2 (AM) and P3 (AM Optimized) relatively to P1 (CM), in terms of impacts on human health, ecosystems quality, resources consumption and climate change

The figure is described in details for each life-cycle stage:

- For the metal production, the impacts of P1 are the highest for the 4 indicators (because of the larger amount of metal required to produce the part compared to P2 and P3).
- For the commodities (P1 is considered not having any commodities), P2 and P3 show additional impacts on each of the 4 indicators. Commodities for AM include argon and the build platform.
- For the manufacturing stage, P1 shows the highest impacts on climate change, human health, resources, but not on ecosystems quality, where P2 and P3 have higher impacts.

This is due to the impacts of the printer, filter and printing in AM which are more damaging to ecosystems quality than the manufacturing of P1 (CM).

- For the post-treatment, P2 and P3 show additional impacts compared to P1 for all indicators. The post-treatment of AM parts (P2 and P3) includes the electricity consumed for the heat treatment stress relief, base separation, surface finishing and platform rectification. The post-treatment of P1 (CM) only includes the electricity consumed for the surface finishing.
- For the use phase, P3 has lower impacts compared to P1 and to P2 on all indicators (because of weight reduction).
- For the waste management, P2 and P3 show additional impacts compared to P1 for all indicators (because of the impacts of hazardous waste treatment).

To follow on the previous description, the main observation is that in terms of total environmental impacts, P2 and P3 show an improved profile on human health and resources compared to P1, but not on ecosystems quality. For the former damage category, the shift of ranking between scenarios observed is mainly due to the impacts related to the AM technology. In fact, the electricity consumed is more important for P2 and P3 because AM is more energy intensive. Also, the electricity production shows that land transformation is the highest elementary flow contributing to the damages on ecosystems quality. It is also the case for the forest transformation elementary flow contributing to the printer impacts on ecosystems quality. Additionally, it is important to note the following: Dandres (CIRAIG, 2018) initially modelled most of the processes as occurring in Quebec. The results were characterized through IMPACT 2002+ (Jolliet et al., 2003) and did not show any shift in the ranking for P1, P2 and P3 in terms of damages to ecosystems quality. However, the LCA model constructed for the purpose of this project used deterministic and probabilistic values from the precalculated aggregated datasets (Lesage et al., 2018) characterized through ReCiPe 2008. For technical reasons only, some processes were substituted by other processes from the "RER" and "GLO" regions (mostly for the AM printer and commodities modelling, for example "hot rolling steel (CA-QC) processing). Although IMPACT 2002+ and ReCiPe 2008 are two different impact assessment methods, the use of processes from different regions could be the main reason why P2 and P3 have greatest impacts on ecosystems quality compared to P1.

The second important point is that human health impacts present the highest reduction potential. They are dominated by the impacts of metal production. These are lessened in AM parts (P2 and P3) because of the reduction in metal required for their production compared to P1. The environmental improvement due to metal saving is supported by the calculation of the buy-to-fly ratio (mass of raw material used over mass of final component, refer to the literature review, section 2.1.5). It is found to be around 4:1 for AM parts (P2 and P3) whereas around 20:1 for P1 (CM).

Third, P3 is 15% lighter in weight compared to P2 and P1 because of its optimized topology. Therefore, it shows an improvement for each of the indicators due to the lower use phase impacts. Since P2 has the same mass as P1, it consumes the same amount of fuel throughout the aircraft lifetime (there is no impact reduction due to the use phase compared to P1).

5.1.2 Environmental profile at midpoint level (ReCiPe 2008, IPCC 2013)

As a reminder, the contribution of climate change to human health and ecosystems quality from ReCiPe is subtracted and IPCC 2013 is used instead to represent the impacts on climate change.

In Figure 5.3, the environmental profile at midpoint level shows that the natural land transformation is the most important contributor to damages on ecosystems quality for P3 (AM Optimized). It is due to inputs from nature such as "transformation from forest", mostly from the "on-shore oil and gas production" process. The PM formation midpoint contributes the most to damages on human health, because of NO_X, SO_2 and particulates emissions. Finally, the fossil depletion midpoint contributes the most to damages on resources, because of crude oil and natural gas. The midpoints contributions to damages for P2 and P3 plotted relatively to P1 are presented in Appendix F.

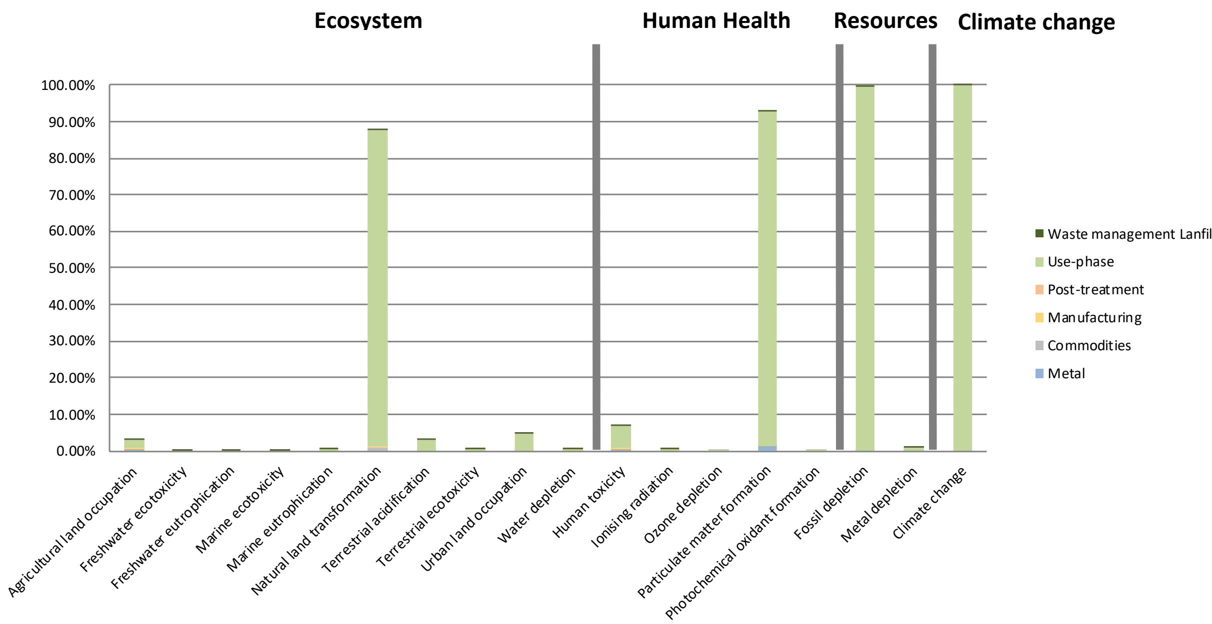


Figure 5.3: Midpoint contribution to damages for P3 (AM Optimized)

5.1.3 Distance-to-target Life-Cycle Assessment

The distance-to-target LCA considers the three emissions of interest for the aeronautical industry: CO_2, NO_x and PM. The results over the complete life-cycle are presented in Figure 5.4. We can also see that the use phase contributes to more than 95% of the environmental impacts on either three of these indicators.

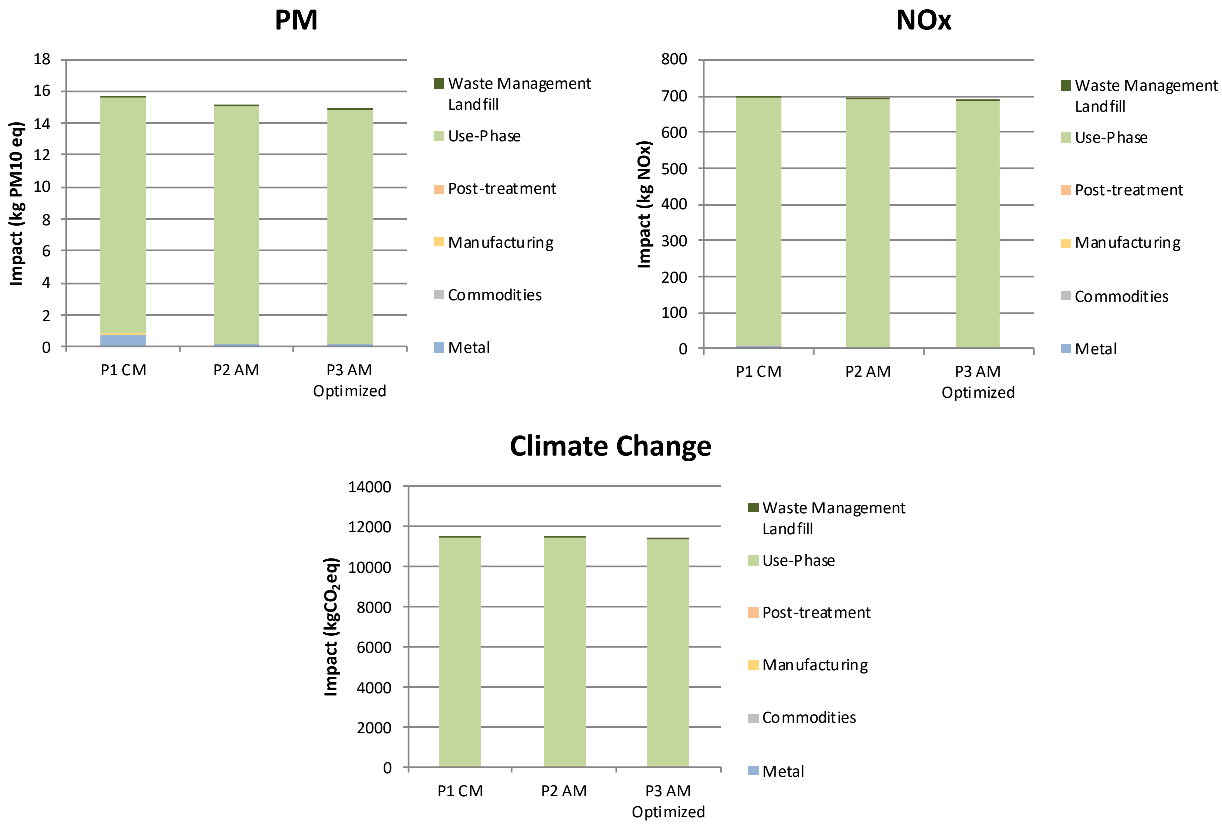


Figure 5.4: Environmental profile of P1 (CM), P2 (AM) and P3 (AM Optimized) in terms of emissions of interest for the distance-to-target approach: nitrogen oxides (NO_x), particulate matter formation (PM) and climate change

Figure 5.5 shows the environmental improvement of scenarios P3 and P2 compared to the base scenario P1. The results show a similar trend to those of the previous section. We first note that P3 contributes to lower emissions of CO_2 , NO_x and PM during the use phase; this is due to its lower (-15%) weight. Moreover, these three emissions also translate an environmental improvement relatively to P1 because of the metal reduction in AM parts (P2 and P3). The total impacts for each indicator show the same ranking for P1, P2 and P3 except for climate change where P2 is slightly worse than P1 (because it has the same use phase emissions, but additional impacts due to commodities and waste management of hazardous waste).

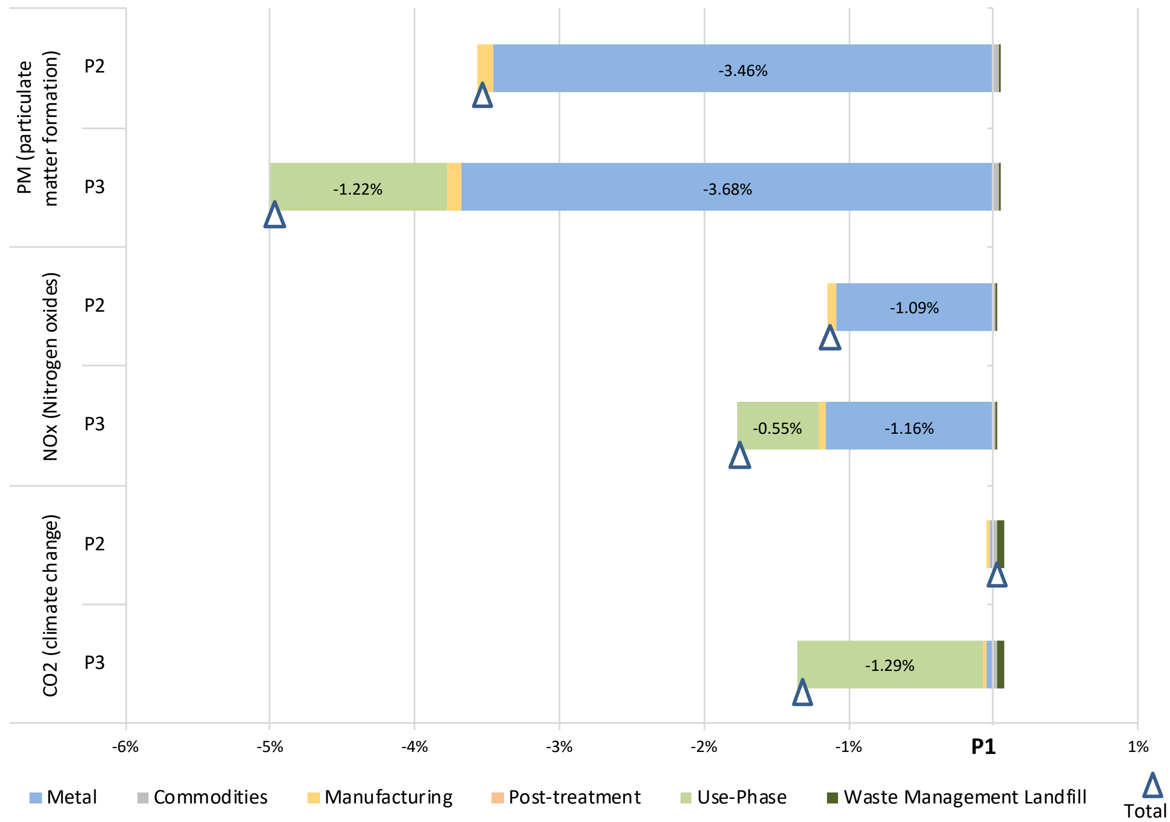


Figure 5.5: Environmental profile of P2 (AM) and P3 (AM Optimized) relatively to P1 (CM), in terms of emissions of interest for the distance-to-target approach: nitrogen oxides (NO_x), particulate matter formation (PM) and climate change.

5.2 Life-cycle Costing

This section presents the results of the life-cycle costing followed by an emphasis on the production costs. The costs correspond to the net present value of the reference year 2018 at a 12% discount rate (including inflation; 9% discount rate net of inflation).

5.2.1 Life-cycle cost

Figure 5.6 below shows the contribution of the production, use and waste management phases to the total life-cycle cost.

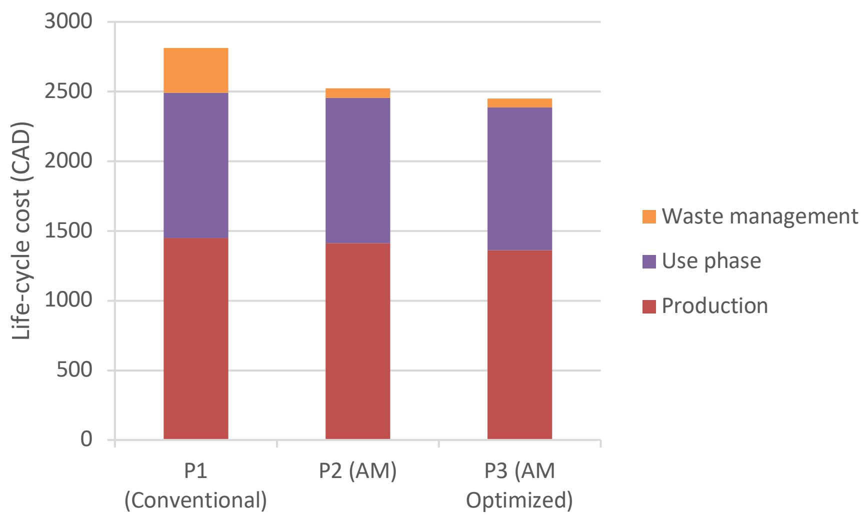


Figure 5.6: Life-cycle cost of scenarios P1 (CM), P2 (AM) and P3 (AM Optimized). Parts are assumed to be made in a batch of 9 and on-demand.

The waste management contribution here includes the waste generated from the manufacturing processes and the waste parts at the end of their lifetime. We can see that waste management is more costly for P1 (CM) than for the P2 and P3 (AM parts), because manufacturing P1 from an initial metal cylinder generates more waste to treat. At end-of-life, the parts are considered to be landfilled. Nevertheless, a sensitivity analysis is performed to see how opting for recycling (and eventually resale of recycled material) may affect the life-cycle impacts and cost (refer to section 5.5.1.1.7).

Also it is clear that the production and use phase costs are significant but it is difficult to see the cost difference between alternatives. This is why Figure 5.7 presents the life-cycle cost of P2 and P3 relatively to P1. A negative value translates a cost reduction.

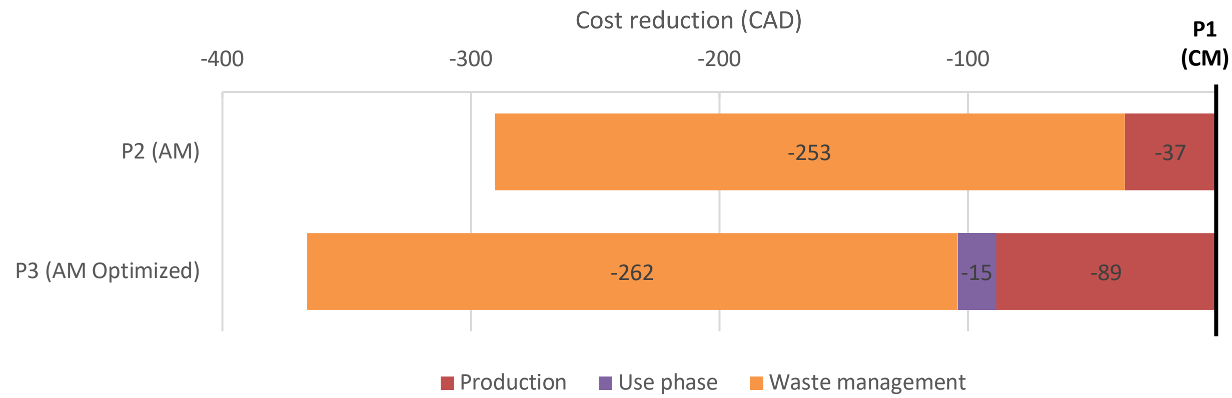


Figure 5.7: Life-cycle cost reduction potential of P2 (AM) and P3 (AM Optimized) relatively to the base scenario P1 (CM)

P2 is 290$ cheaper than P1, whereas P3 is 366$ cheaper compared to P1 because it shows an additional cost reduction due to the use phase and waste management. In fact, because of topology optimization, P3 is lighter in weight than P1 and P2. Thus, it consumes less fuel during the aircraft operation (15$ cost reduction). Its associated life-cycle waste quantity (from the production and at its end-of-life) is lower.

Furthermore, as the production cost almost equals half of the life-cycle cost (Figure 5.6), we look further into the production phase in the next section.

5.2.2 Production cost

Additive manufacturing production costs here are broken down into 6 categories (Figure 5.8). Direct costs account for the powder, energy and argon costs. Machine cost considers the hourly rate cost of the AM machine and maintenance costs includes the cost of filters, build plate, recoater and sieve used to separate the components from the build plate. Labor cost is related to the programming time needed to convert the CAD file into a EOSJZ file (file adapted for the printer), the setup of the build plate, and the monitoring of the printing process. Stress relief heat treatment are part of the post-process cost and finally, post-AM machining includes the aggregated cost of material, labor and machine involved to subtract machine allowances in AM parts using conventional manufacturing (post-AM machining cost contribution is similar to that of CM parts, refer to Figure 5.9).

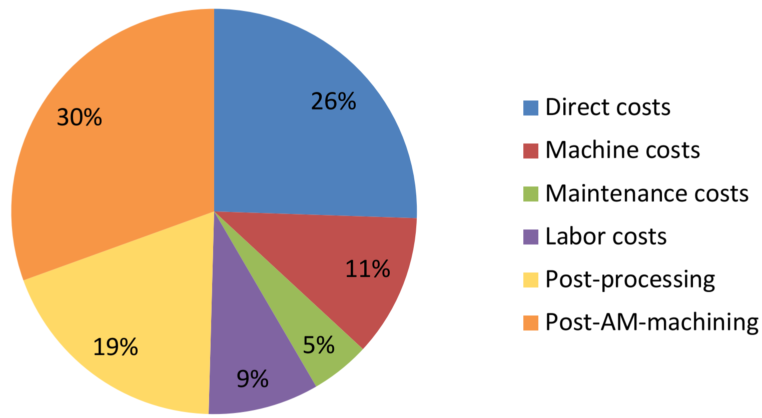


Figure 5.8: Production cost repartition for the additive manufacturing parts P2 (AM) and P3 (AM Optimized)

We can see that half of the production cost is due to post-printing activities. As the technology reaches higher maturity levels on the market, this cost is expected to decrease, hence reducing the total production cost of AM parts. Additionally, the powder is currently expensive because of its long and costly production process but is expected to decrease with technology advancements.

Figure 5.9 shows the contribution of material, labor and machine costs to the production cost of completely conventionally manufactured parts.

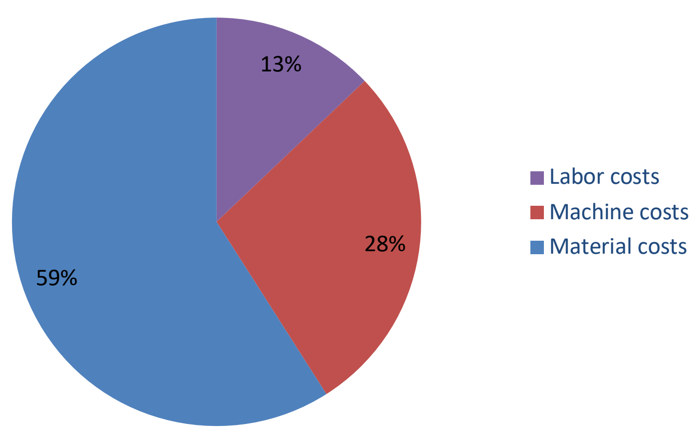


Figure 5.9: Production cost repartition for the conventional manufacturing part P1 (CM)

Labor cost takes into consideration the programming time, the production of the 1st component (takes more time than components produced in series because the production is not yet stabilized), and the setup. Machine cost accounts for the hourly rate of the machine (including maintenance), the cost per manufacturing operation obtained with the Walter online GPS tool[12] (Appendix B). Finally, material costs include raw material and mounting template costs (coolant is also considered but found to be negligible).

5.3 Eco-efficiency

The eco-efficiency diagram below combines the environmental and economic dimensions (Figure 5.10). Points P2 and P3 are placed relatively to the diagram centre representing the base scenario P1. The environmental dimension builds on distance-to-target results and the cost dimension uses life-cycle costing results. Each score is normalized with reference to the aircraft life-cycle impacts and costs, respectively. Therefore, the diagram shows on the x-axis percentage units of environmental improvements, and on the y-axis percentage units of cost reduction.

We can see that the AM optimized part (P3) dominates the two others scenarios, i.e. it is "better" on both dimensions. Therefore P3 is more eco-efficient than P1 and P2. This is true for a trade-off of 1 and for all other possible trade-offs. Although P2 is dominated by P3, it is more eco-efficient than P1.

[12] https://gps.walter-tools.com/touchtime/walter#/home

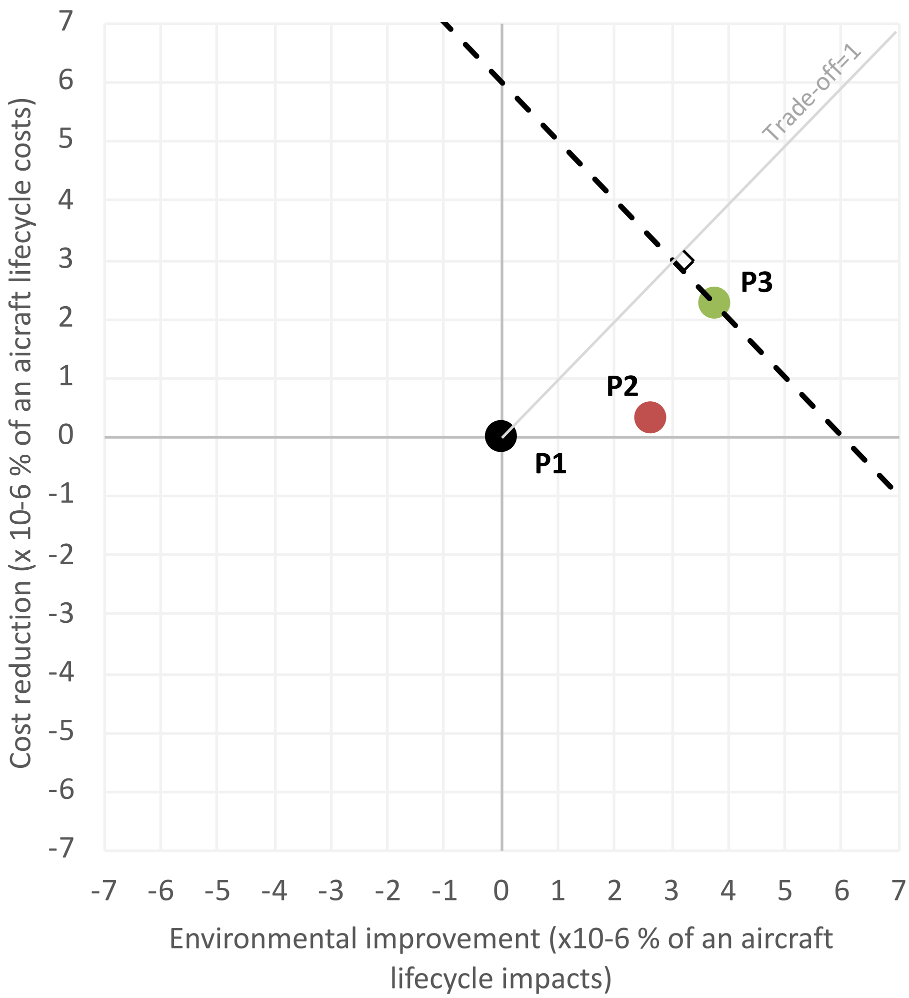


Figure 5.10: Eco-efficiency diagram

5.4 Uncertainty analyses

This section shows the results of the probabilistic uncertainty analyses for the LCA, LCC and EE.

5.4.1.1 Significance of the difference between scenarios in life-cycle assessment

The first result of interest is a probabilistic distribution of results by life-cycle stage and for the complete life-cycle. It can show the variation and magnitude in impacts uncertainty between scenarios and life-cycle stages, underlining those that contribute the most to the total life-cycle uncertainty. Figure 5.11 represents the box and whiskers chart comparing P1, P2 and P3 in terms of climate change (kg CO_2 eq). The use phase distributions predominate over the other life-cycle stages because of its contribution to more than 95% of the total life-cycle impacts (as seen in deterministic results). Deterministic results presented in the previous section indicate that P3 has lower impacts than P2 and P1. However, due to their uncertainty, this ranking should not be validated. In addition to that, the life-cycle impact distributions show a similar spread for the three scenarios. Hence, one cannot make a difference about the superiority of an option over the other in terms of CO_2 eq.

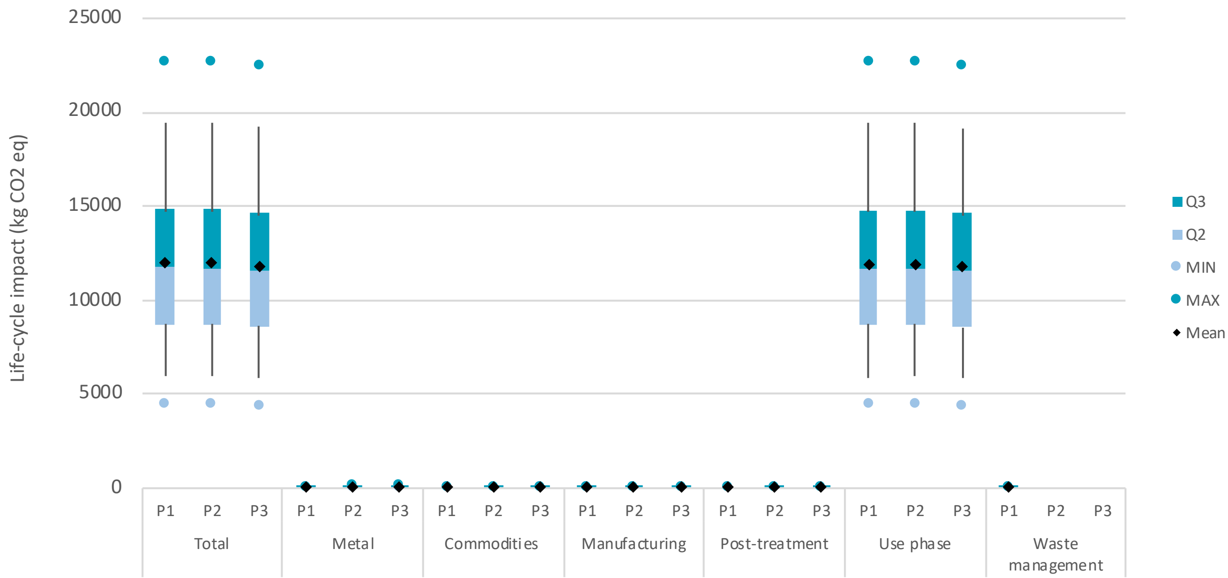


Figure 5.11: Box and whisker chart representing life-cycle impact in terms of kg CO_2 eq distribution for the complete life-cycle (left) and the distribution by life-cycle stage (right). Results are presented with a confidence interval of 95%. The whiskers represent the 2.5e and 97.5e centile. The box is split by the median and its bottom and top represent the 2nd and 3rd quarters respectively. Outliers are excluded.

In consequence, scenarios are compared under uncertainty by quantifying the differences between them. In other words, the significance of the difference between them is calculated, by counting throughout the Monte Carlo iterations, the frequency at which one scenario is better than another (Figure 5.12). On 1000 iterations, the CO_2 emissions of P3 are 100% of the time lower than those of P1 and P2. Also, the CO_2 emissions of P2 are 85% of the time lower than those of P1. Therefore, despite the CO_2 emissions uncertainty, communicating this significance percentage gives reliability for the scenarios comparison and ranking.

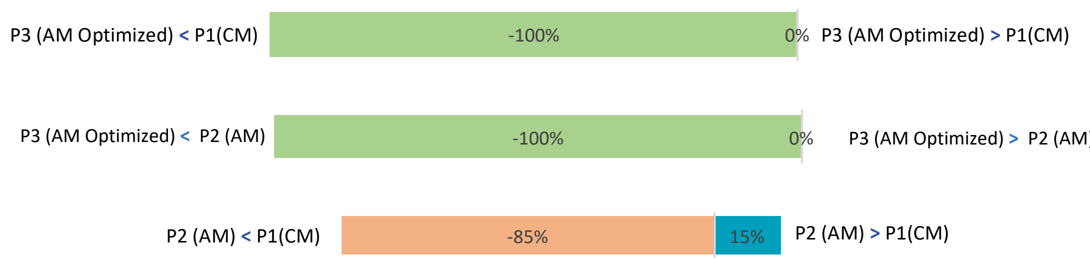


Figure 5.12: Probability of a scenario being better than another in terms of environmental impact (CO_2 eq) for P1 (CM), P2 (AM) and P3 (AM Optimized)

The box and whiskers results show the same trend for the human health, resources, ecosystems quality, NO_x and PM indicators. The significance of the difference analysis confirms the deterministic results (P3 and P2 are more environmentally performant than P1 on all indicators except ecosystems quality) (Appendix E).

5.4.1.2 Significance of the difference between scenarios in life-cycle costing

5.4.1.2.1 Life-cycle cost

The probabilistic distributions obtained from 1000 Monte Carlo life-cycle cost results are presented in Figure 5.13. This figure shows that the datasets are evenly distributed. Therefore no conclusion may be drawn on the best cost option on neither of the life-cycle stages. Consequently, the significance of the difference between P1, P2 and P3 (Figure 5.14) is performed.

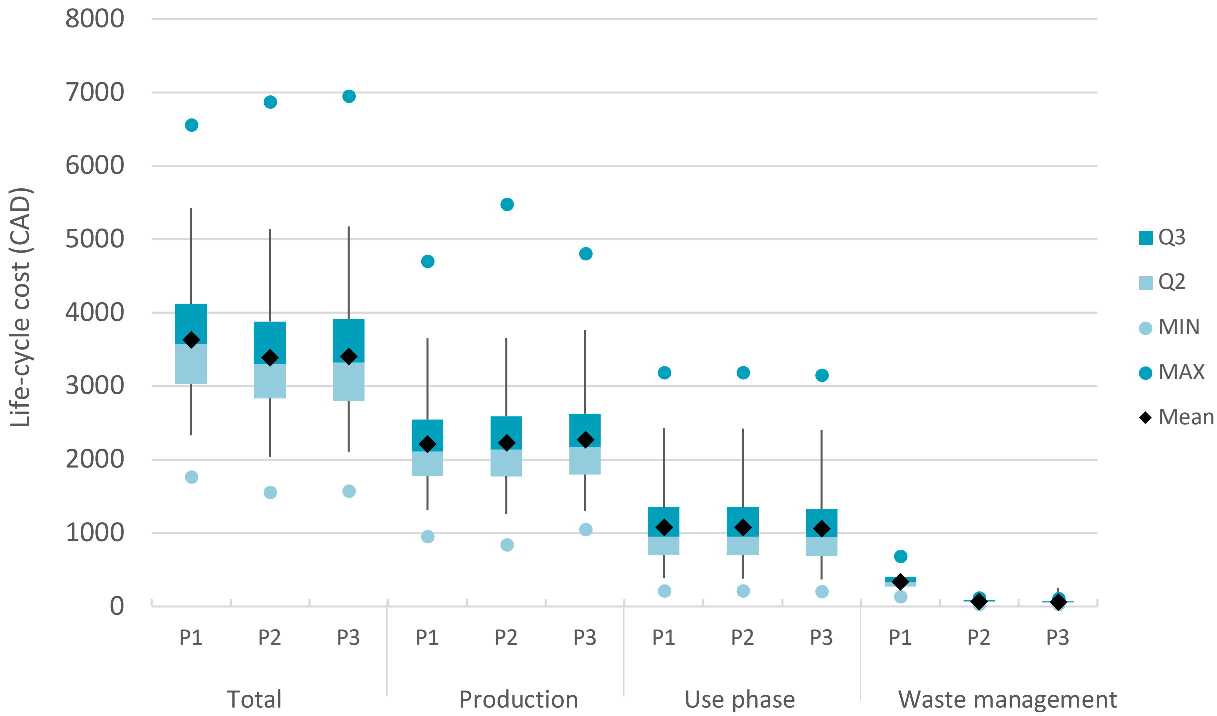


Figure 5.13: Box and whisker chart representing life-cycle cost distribution for the complete life-cycle (left) and the distribution by life-cycle stage (right). Results are presented with a confidence interval of 95%. The whiskers represent the 2.5e and 97.5e centiles. The box is split by the median and its bottom and top represent the 2nd and 3rd quarters respectively. Outliers are excluded.

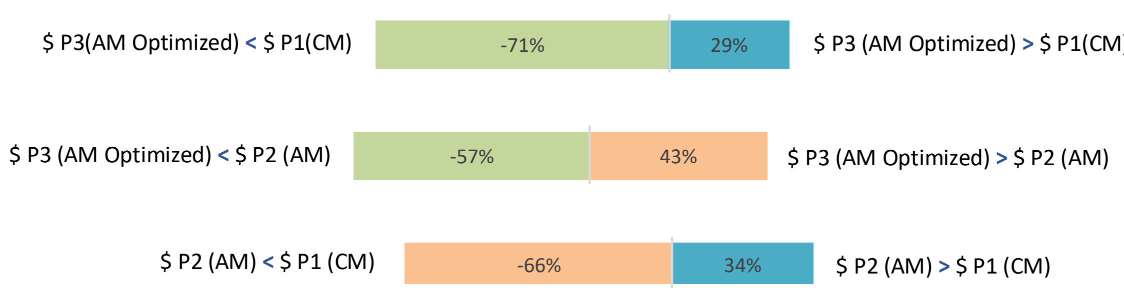


Figure 5.14: Probability of a scenario being better than another in terms of life-cycle cost (CAD) for P1 (CM), P2 (AM) and P3 (AM Optimized)

We can see that there are 71% chances of P3 having a lower life-cycle cost compared to P1 and 57% chances of being lower than P2.

Although these percentages are not discriminatory, the decision is left to the decision-maker's risk tolerance. Performing a global sensitivity (section 5.5.1.2.3) analysis can help identify the main uncertainty contributors in order to try reducing their uncertainty; in doing so, the significance between results is expected to become more decisive.

5.4.1.2.2 Production cost

The production cost distributions (Figure 5.15) also do not allow the formulation of conclusions and is followed by a calculation of the significance of the difference between P1, P2, and P3 (Figure 5.16).

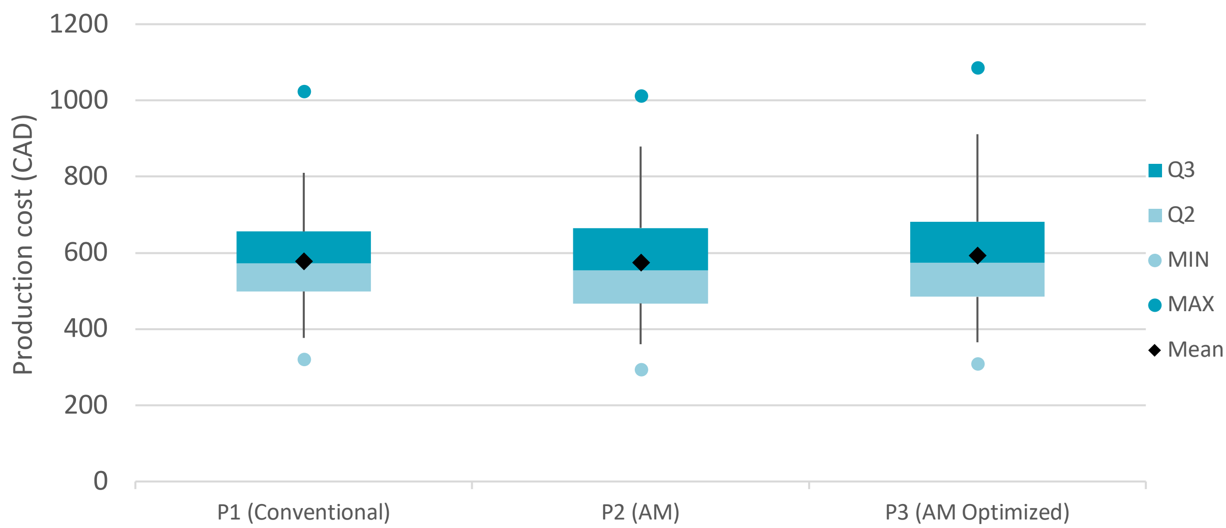


Figure 5.15: Box and whisker chart representing production cost distributions. Results are presented with a confidence interval of 95%. The whiskers represents the 2.5e and 97.5e centiles. The box is split by the median and its bottom and top represent the 2nd and 3rd quarters respectively. Outliers are excluded.

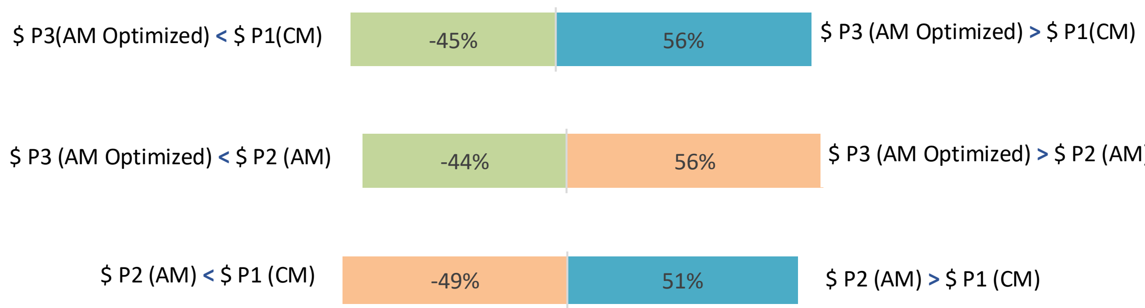


Figure 5.16: Probability of a scenario being better than another in terms of production cost (CAD) for P1 (CM), P2 (AM) and P3 (AM Optimized)

The results shows that the probability of P3 being advanced as a more cost-efficient scenario compared to P2 and P1 on 1000 Monte Carlo iterations is lower than 50%. This is important to underline because the production cost variability affects the overall life-cycle cost uncertainty. The former statement is further confirmed in the global sensitivity analysis section.

5.4.1.3 Significance of the difference between scenarios in eco-efficiency

The eco-efficiency diagrams usually present deterministic results for the points coordinates representing different alternatives. As a reminder, each point located on the diagrams here uses as x-coordinate, the environmental impact improvement relatively to the base scenario P1 (normalized with reference to the aircraft life-cycle impacts), and as y-coordinate, the cost reduction relatively to P1 (normalized with reference to the aircraft life-cycle cost). Nevertheless, in a probabilistic approach, a distribution of possibilities for each dimension can be observed from the 1000 Monte Carlo iterations. Therefore, the deterministic results presented disregard the risks that another scenario may be more eco-efficient than the one claimed by its deterministic location on the graph. Presenting the uncertainty in the eco-efficiency diagram helps visualizing such variability of results and supporting decisions made while considering the uncertainty.

The eco-efficiency diagram in Figure 5.17 shows the thousand Monte Carlo (x,y) coordinates for P3. The deterministic coordinates of P3 are defined as the mean value of the cost and environment distributions distinctly. First, the results distribution for the environmental improvement indicate that P3 is always more environmentally performant than P1. Second, we can observe that the uncertainty on the y-axis is greater than the uncertainty on the x-axis. In other words, the spread of the cost reduction results is greater than that of the environmental improvement. Refining the variability of input parameters involved in the life-cycle cost calculation would decrease the spread of results and would increase the ease to make a decision.

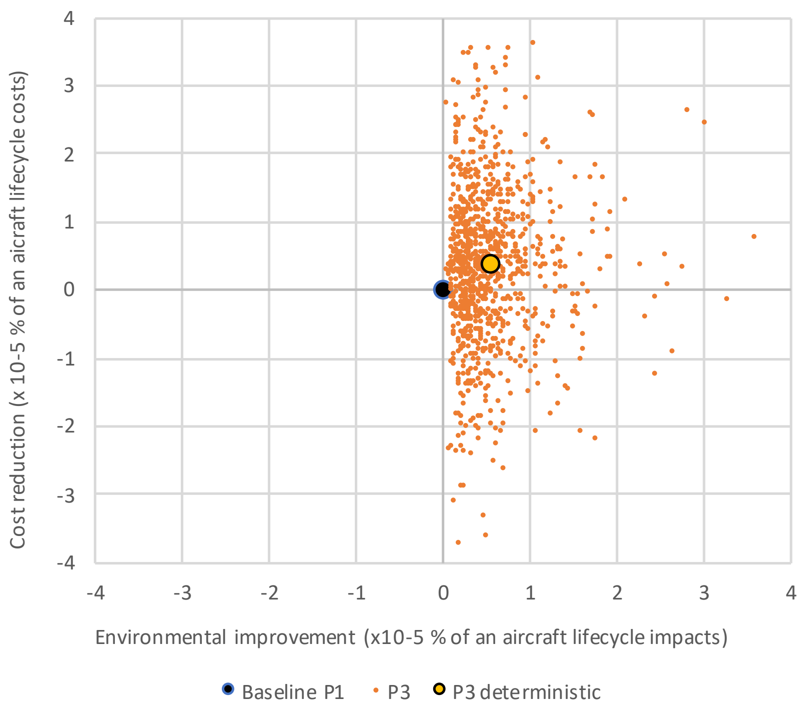


Figure 5.17: Eco-efficiency diagram illustrating the probabilistic and deterministic eco-efficiency results of P3 (AM) relatively to P1 (CM)

Consequently, accounting for the uncertainty, it is clear that P3 is not always the most eco-efficient scenario. Nevertheless, we count the number of iterations where P3 has a greater eco-efficiency than P1, for a trade-off of 1 (the eco-efficiency value is calculated using equation 17) (Figure 5.18).

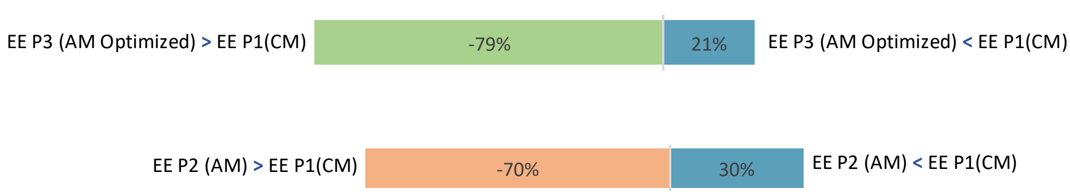


Figure 5.18: Probability of a scenario being better than another in terms of eco-efficiency for P1 (CM), P2 (AM) and P3 (AM Optimized) when the trade-off is set to 1

The results show that throughout 1000 Monte Carlo iterations, P3 has 79% chances of being more eco-efficient than P1. Thus, this percentage can be used as a support for decision-making.

If we consider the trade-off value to be stochastic, the environmental and cost dimensions do not necessarily have the same importance in decision-making, because the trade-off value is not always equal to 1. Nonetheless, P3 is still more eco-efficient than P1 74% of the time (Figure 5.19).

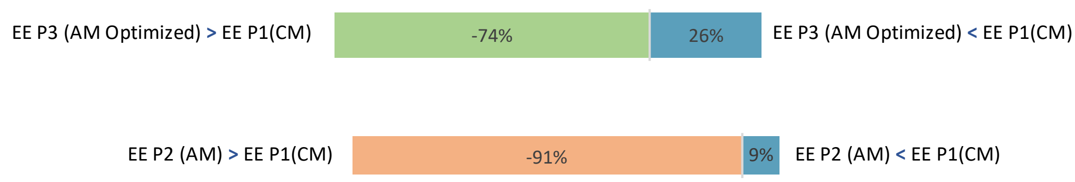


Figure 5.19: Probability of a scenario being better than another in terms of eco-efficiency for P1 (CM), P2 (AM) and P3 (AM Optimized) when the trade-off is considered stochastic

5.5 Sensitivity analyses

5.5.1.1 Local sensitivity analyses

5.5.1.1.1 Comparison between standard and distance-to-target LCA approaches: ranking between scenarios in deterministic results

Table 5.1 shows scenarios P1, P2 and P3 in function of the 4 damage indicators presented in the LCA section and the 3 emissions indicators used in the distance-to-target approach. This is done in order to confirm whether scenarios keep the same ranking using different environmental indicators. Also, it allows discussing whether the CO_2, NO_x and PM emissions considered by the aeronautical industry are representative enough of the complete environmental profile of the parts.

Table 5.1: Ranking of scenarios in terms of environmental performance, in function of the environmental indicator used (deterministic results)

Indicator / Scenario	P1 (CM)	P2 (AM)	P3 (AM Optimized)
Human health	**3**	**2**	**1**
Ecosystems	**1**	**3**	**2**
Resources	**3**	**2**	**1**
Climate change (CO_2)	**2**	**3**	**1**
NO_x	**3**	**2**	**1**
PM	**3**	**2**	**1**

A ranking of 1 means that the corresponding scenario is the most environmentally performant, i.e. shows the lowest impacts compared to the other scenarios.

Climate change is the only indicator in common in both approaches and shows impact scores ranked as follow: P3 < P1 < P2. In addition, P1 results last in the ranking of the remaining indicators except for ecosystems quality where it shows the lowest impacts. This may be explained as per section 5.1.1; some elementary flows are in fact severely characterized in ecosystems quality compared to other damage categories. Therefore, we can conclude that P1, P2 and P3 do not show the same ranking using different environmental indicators such as ecosystems quality. Also, the CO_2, NO_x and PM emissions considered by the aeronautical industry are not representative enough of the complete environmental profile of the parts.

5.5.1.1.2 Sensitivity analysis of the life-cycle impacts to the batch size

Figure 5.20 shows the effect of batch size on the life-cycle impacts of P2 and P3 relatively to P1. The results presented are for a batch size of 1. We can see that the commodities, manufacturing and post-treatment impacts are significantly increased for P2 and P3 relatively to P1. This is mainly because these impacts are only allocated to one part instead of 9. A small batch size emphasizes the life-cycle impacts per part, and is therefore not desirable at the production level for AM. In addition, P1, P2 and P3 keep the same ranking towards the 4 environmental indicators (compared to the impacts for a batch of 9).

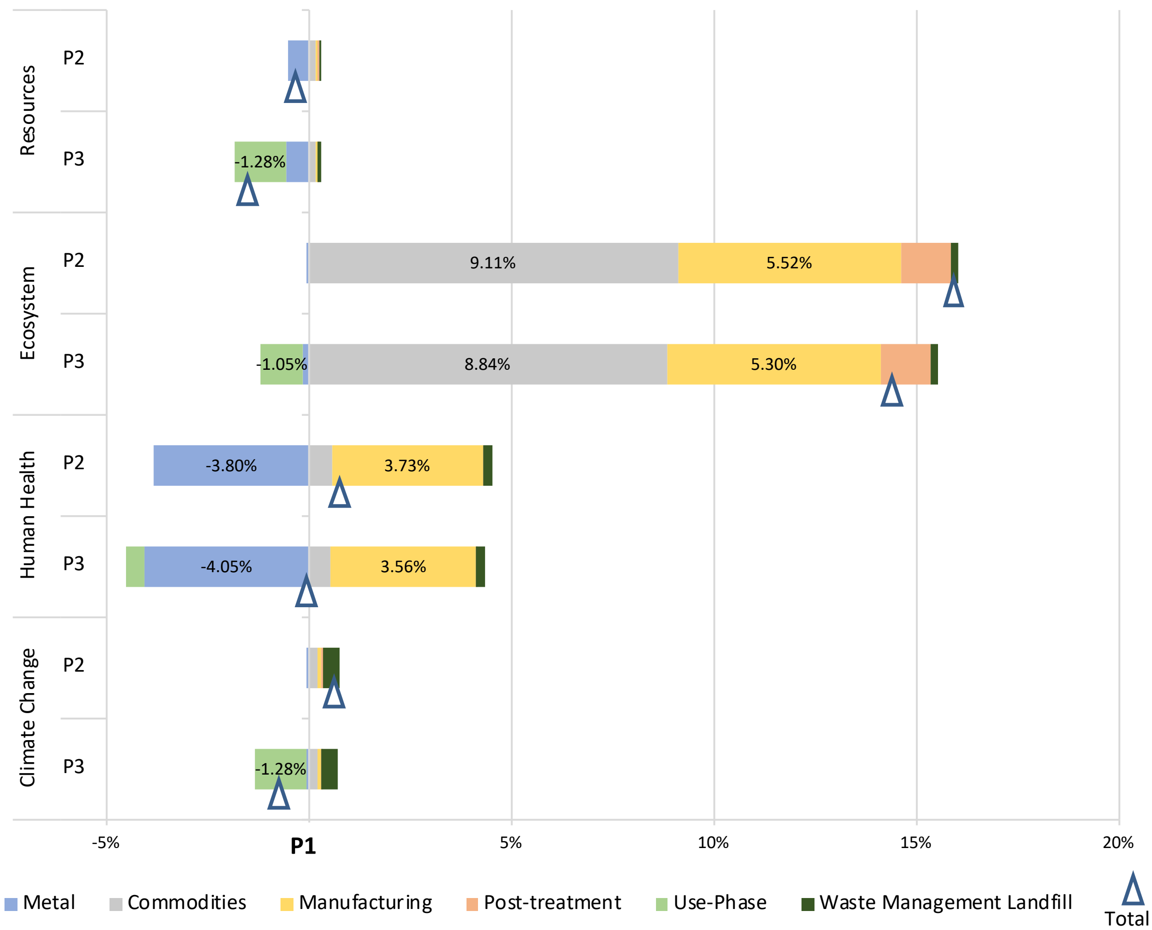


Figure 5.20: Sensitivity of the life-cycle impacts to the batch size (1 instead of 9). The impacts of P2 (AM) and P3 (AM Optimized) are plotted relatively to P1 (CM)

5.5.1.1.3 Sensitivity analysis of the production cost to the batch size

A local sensitivity analysis of the production cost to the batch size is performed. We consider batch sizes of 1, 9 and 90 and break the production cost (unit cost) as following (Figure 5.21):

- For AM parts (P2 and P3), the production cost is equal to the cost of printing (AM) and post-AM machining operations (CM).
- For the CM part (P1), the production cost is equal to machining operations.

- Machining operations include the machining of the 1st component and that of the other components. In fact, the 1st machined component is assumed to take up to the quadruple of the time spent to manufacture the parts in series (parts in series are the parts produced in volume once the production is stabilised).

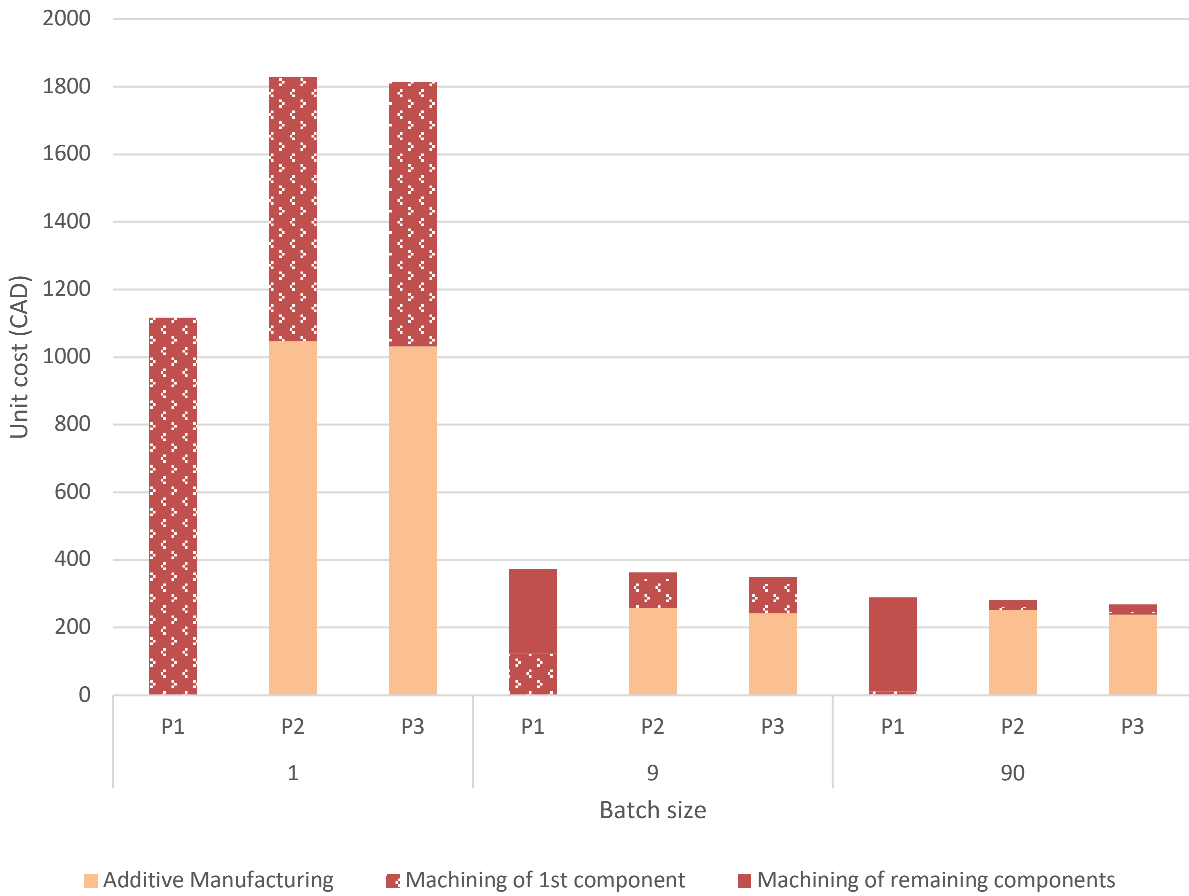


Figure 5.21: Unit production cost variation with batch size for P1 (CM), P2 (AM), P3 (AM Optimized)

It is noticeable that batch production decreases the cost because infrastructure and labor costs are distributed over the number of parts, therefore the bigger the batch size, the lower the costs (for both AM and CM). It is also the case for the 1st component machining cost which is palliated with an increasing production volume.

We can see that at low production volumes (batch size=1), the AM parts cost (P2 and P3) would be significantly lower if the post-AM machining operations could be reduced. Also, we can note that with an increasing batch size, the machining cost per part, for either AM (P2 and P3) or CM

(P1), decreases. Nevertheless, for the AM parts, this decrease in the cost of machining is more significant than the decrease in the cost of AM.

5.5.1.1.4 Sensitivity analysis of the life-cycle cost to the batch size and production scenario

A sensitivity analysis of the life-cycle cost to the production scenario is carried out (Figure 5.22). The part, once installed in the aircraft, wears after a specific period of time. Therefore, spare parts must be produced to replace the original one when needed. The production of all parts required for maintenance may be produced at the same time (at reference year 2018), or they may be produced on-demand, i.e. whenever needed. Therefore, 4 production cases for AM are compared to understand how they affect the life-cycle cost:

a) Spare parts are produced on-demand, batch 1. For AM, each part is printed alone on the build plate. For CM, one part is made from a metal cylinder.

b) Spare parts are produced on-demand, batch 9. For AM, each part is printed along with other components in the same batch (on the same build plate). For CM, one part is made out of a metal cylinder and is part of a batch (9 parts manufactured in series).

c) Spare parts are produced at first, batch 1. For AM, each part is printed alone on the build plate. For CM, one part is made from a metal cylinder.

d) Spare parts are produced at first, batch 9. For AM, each part is printed along with the others in the same batch (on the same build plate). For CM, one part is made from a metal cylinder and is part of a batch (9 parts manufactured in series).

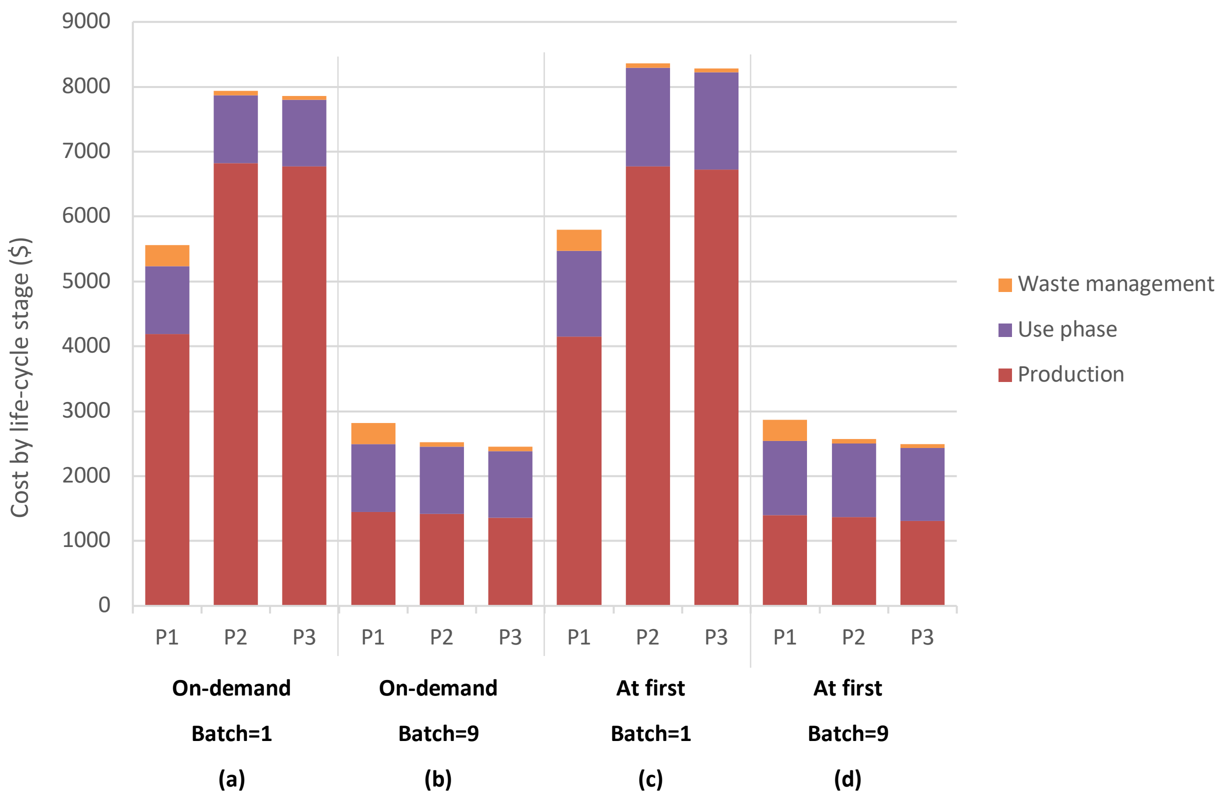


Figure 5.22: Sensitivity analysis of the life-cycle cost to the production scenario for P1 (CM), P2 (AM), P3 (AM Optimized)

Figure 5.22 shows a great difference in magnitude between a batch size of 9 and 1, explained previously as per section 5.5.1.1.3. In addition, in the AM industry, parts are very rarely placed alone on the build plate. Therefore cases (a) and (c) are not very representative of the reality.

Now, comparing scenarios (b) and (d): manufacturing the spare part only when the original one needs to be replaced (b) helps avoiding storage and insurance costs, which are included in the use phase (although not shown in the graph); these costs are inevitable when the parts are produced at first (d) and may be distinguished in Figure 5.23 (P2 usually has the same use phase cost than P1, however we can see a slight contribution of the use phase to the life-cycle cost of P2 in scenario (d), due to storage and insurance costs). Furthermore, the production of spare parts on-demand lowers the net present value of such an expenditure made at a later time.

In the aeronautical industry, parts are more likely to be printed on-demand, therefore it is more relevant if a spare part is produced at the time of replacement rather than at first (along with the production of the original part).

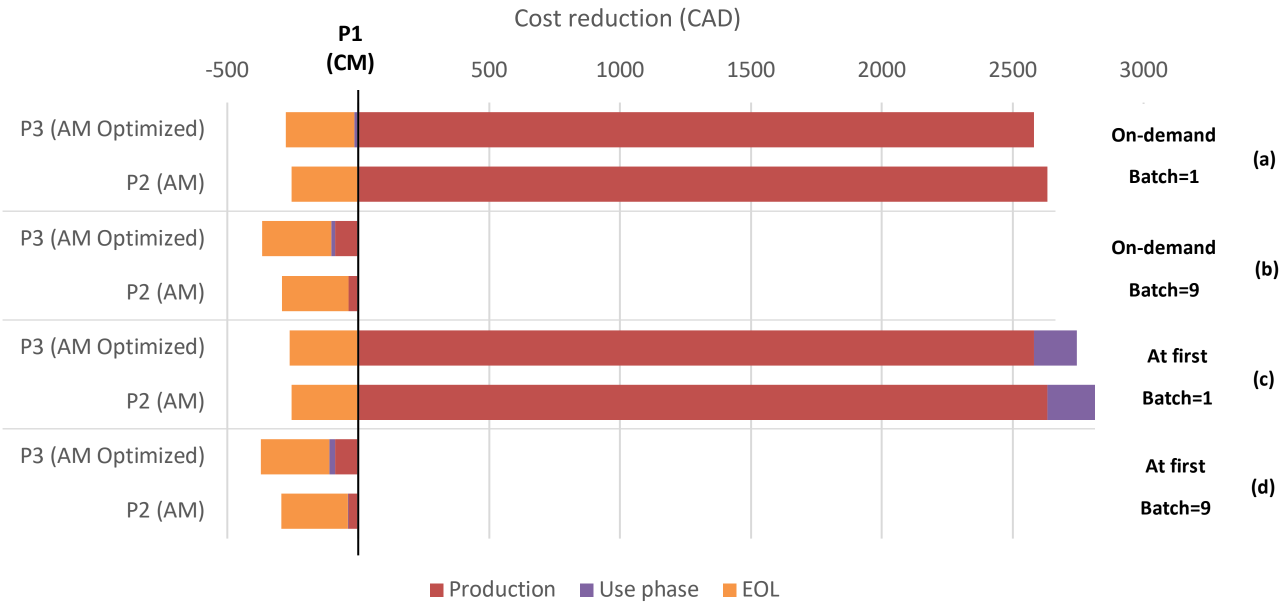


Figure 5.23: Sensitivity on the life-cycle cost of production scenarios (batch size and timing of the production of spare parts). The relative difference of P2 (AM) and P3 (AM Optimized) is plotted relatively P1 (CM).

5.5.1.1.5 Sensitivity analysis of life-cycle cost to the discount rate

A sensitivity analysis to the discount rate is performed in order to evaluate the influence of time on the life-cycle cost results. The reference scenario is set at a discount rate of 12% (including inflation), and the production of parts is defined in this section as an on-demand production, i.e. occurs at different moments in the aircraft lifetime.

Discounting accounts for the fact that a dollar today worth more than a dollar in ten years from now (even if inflation is disregarded), and that is because more importance is given to the present time and to the productive uses we can make of an invested dollar. Also, amounts of money paid today do not have uncertainty as is the case for future expenses. Because future cash flow carry a risk that present expenditures do not, we must discount future cash flow to compensate us for the risk we take in future payments. Thus, Figure 5.24 shows that when the discount rate is set to 0%, the life-cycle cost is significantly higher. In fact, this means that one dollar paid today is worth the same value than one dollar paid at the aircraft end-of-life year. A discount rate of 15% decreases the costs, though reducing the relative life-cycle cost difference between P1, P2 and P3. The latter can be observed in Figure 5.25.

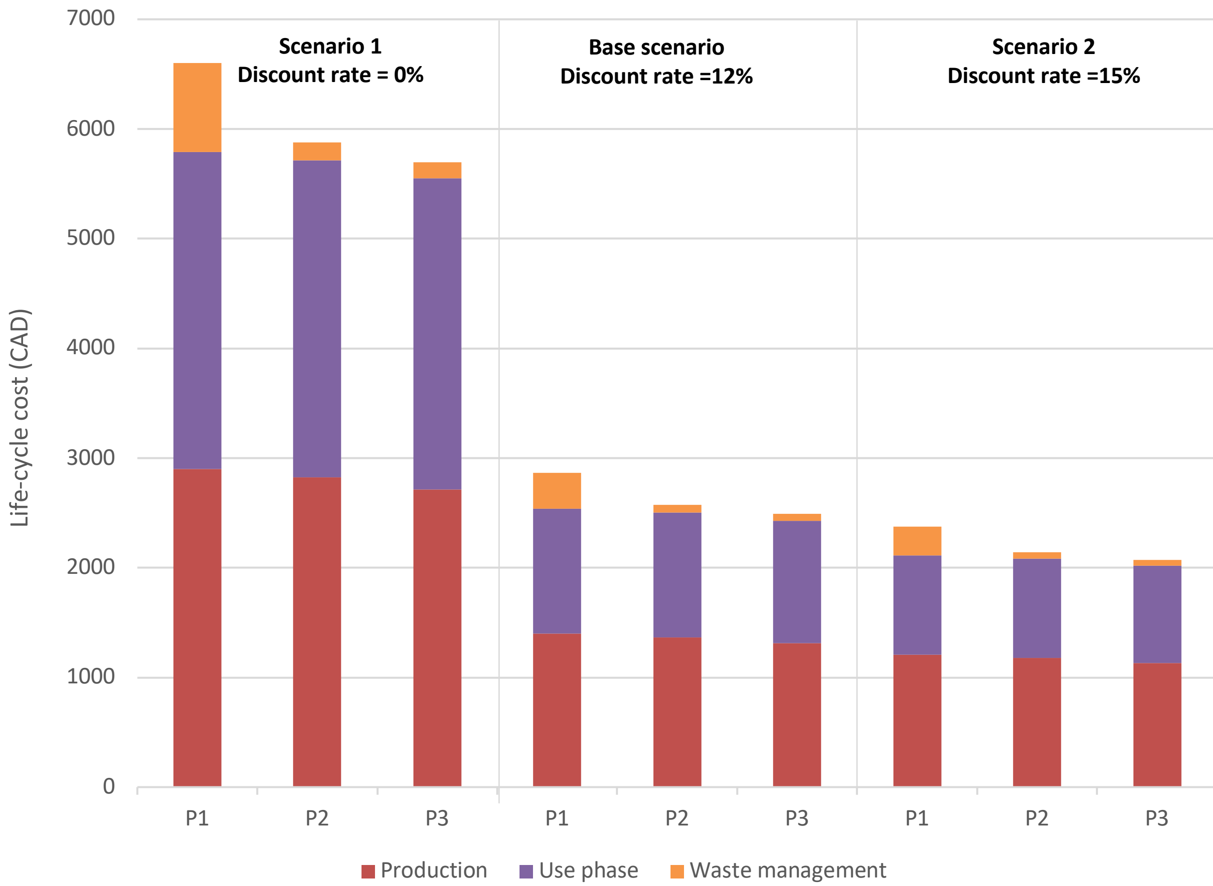


Figure 5.24: Sensitivity analysis of the life-cycle cost to the discount rate for P1 (CM), P2 (AM), P3 (AM Optimized)

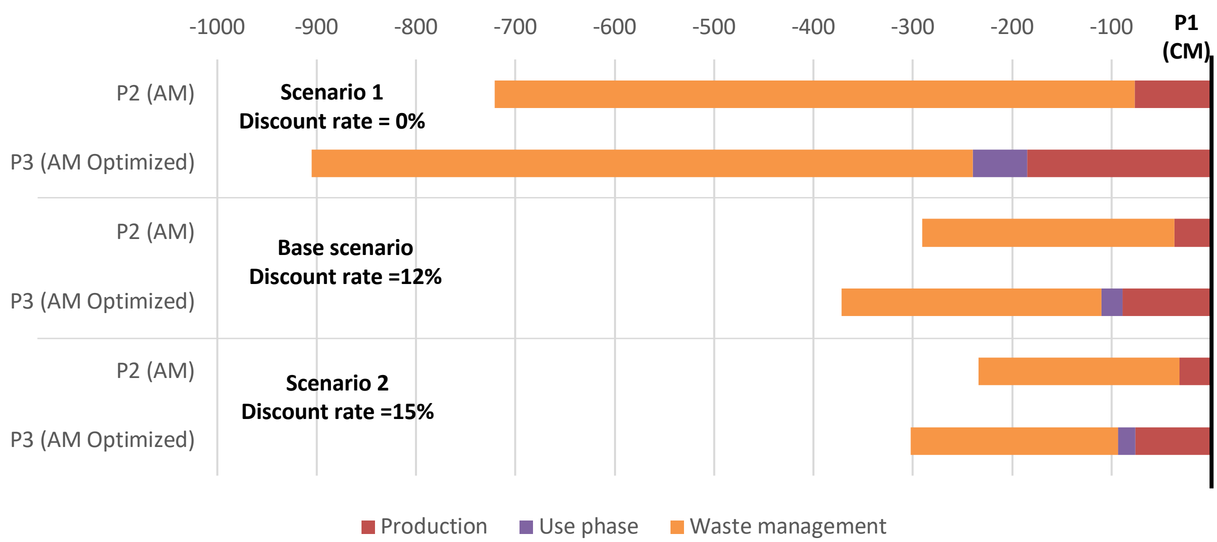


Figure 5.25: Sensitivity analysis of the life-cycle cost of P2 (AM) and P3 (AM Optimized) relatively to P1 (CM) to the discount rate

We notice that setting the discount rate to 0% increases the cost reduction potential of P3 and P2 compared to P1 (additional 430$ reduction for P2 and 532$ for P3 compared to the scenario with a 12% discount rate). For a discount rate of 15%, the ranking of P1, P2 and P3 stays the same although the cost reduction enabled relatively to P1 is less significant.

5.5.1.1.6 Sensitivity analysis of eco-efficiency to the batch size

The batch size during production changes the eco-efficiency results such as presented in Figure 5.26. We can see that for a trade-off of 1, the most-eco-efficient scenario is the base scenario P1. Nevertheless, P3 demonstrates an improved environmental performance compared to P1 and according to ISO 14045 (2012), P1 shall not be claimed as more eco-efficient, because of its worse environmental performance. The figure also indicates that P1 and P3 are iso-eco-efficient for a trade-off of 0.2. This means that P3 would be the most eco-efficient scenario if at least 5 times more importance was given to the environmental dimension compared to the economic one.

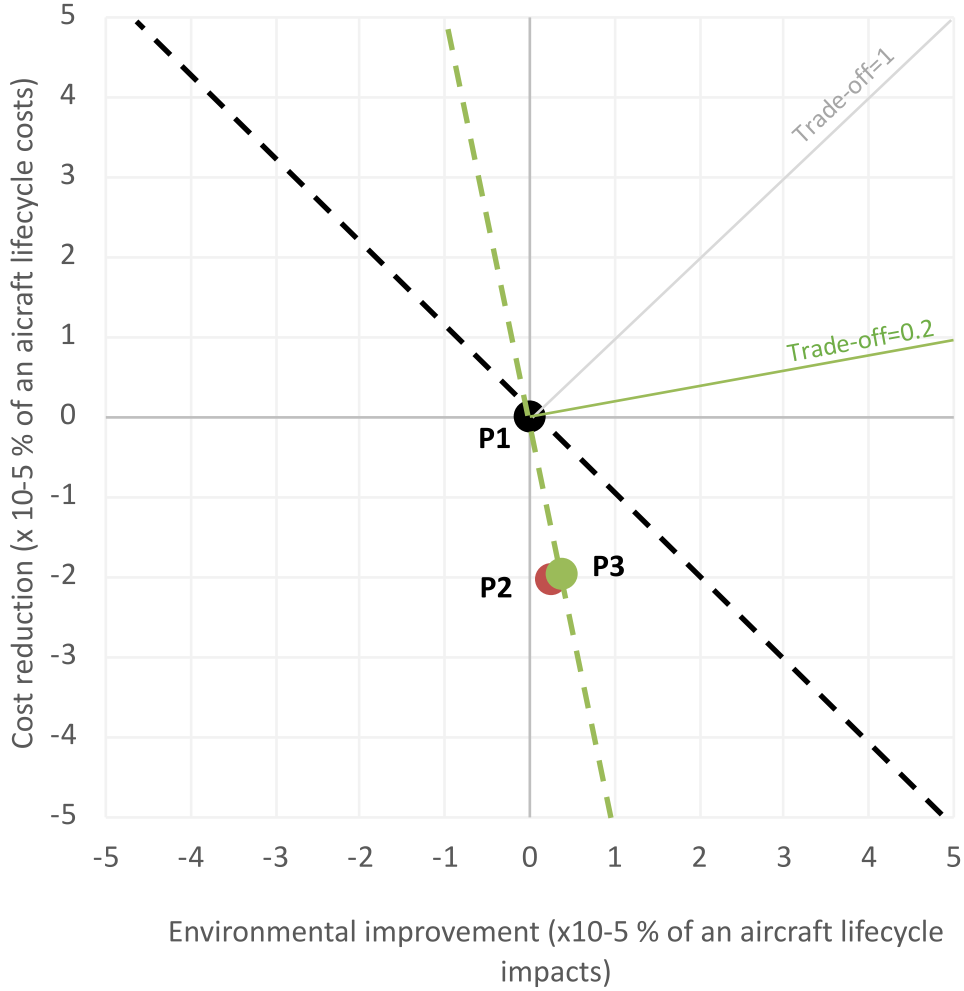


Figure 5.26: Eco-efficiency diagram for a batch size of 1 (instead of 9)

5.5.1.1.7 Sensitivity analysis of life-cycle impacts and costs to recycling and credit to recycling

A sensitivity analysis to recycling and credit to recycling is performed. The life-cycle impacts and costs are slightly improved when recycling is included and that credit is given to the avoided virgin material production (Appendix E).

5.5.1.1.8 Sensitivity analysis to the fuel consumption model approach

The difference in the fuel consumption modelling affects indeed the results. In fact, adopting the approach of saying that the fuel consumption increases proportionally to the increase in aircraft mass increases the cost and environmental impacts of the parts and would further emphasize the improvement of P3 compared to P1 (Appendix E).

5.5.1.2 Global sensitivity analyses

Global sensitivity analyses (GSA) results show a ranking of influential parameters in LCA, LCC and EE in order to inform on which ones to select for data refinement. The analyses are based on the Spearman rank order coefficient, which measures the strength of the correlation between the ranked iterations of input parameters and the ranked iterations of the outcome (LCA, LCC, EE). The coefficient may either be positive or negative, describing an increasing or decreasing relationship between each input parameter and the outcome. The closer the coefficient is to -1 or 1, the more sensitive is the outcome uncertainty to the corresponding input parameter.

Although the figures show sorted parameters, this is only done in order to easily distinguish the parameters with high Spearman coefficients. In no case do we attempt to compare parameters among each other. In fact, because it is based on the rank rather than raw data, the Spearman coefficient does not indicate the relationship between input parameters, but only their respective relationship with the outcome. Additionally, it may underestimate or overestimate this relationship. Conclusions derived using this coefficient might be misleading because low effect may be over-estimated as interactions between variables may be high (Saltelli et al., 1999). Therefore, a conservative approach is adopted; only parameters with a Spearman rank order coefficient greater than 0.2 and lower than -0.2 (medium and high correlations) are considered.

5.5.1.2.1 Global sensitivity analysis of the life-cycle assessment

Figure 5.27 shows a Spearman rank order coefficient of 0.93 for the distance travelled by the aircraft. It is the only parameter indicating a significant enough coefficient value for interpretation. Therefore, the number of kilometres travelled by the aircraft over its lifetime is clearly the priority parameter to refine in order to reduce the uncertainty on the life-cycle impacts results. The analysis is done for the climate change impacts but yields the same conclusion for the impacts on the other environmental indicators.

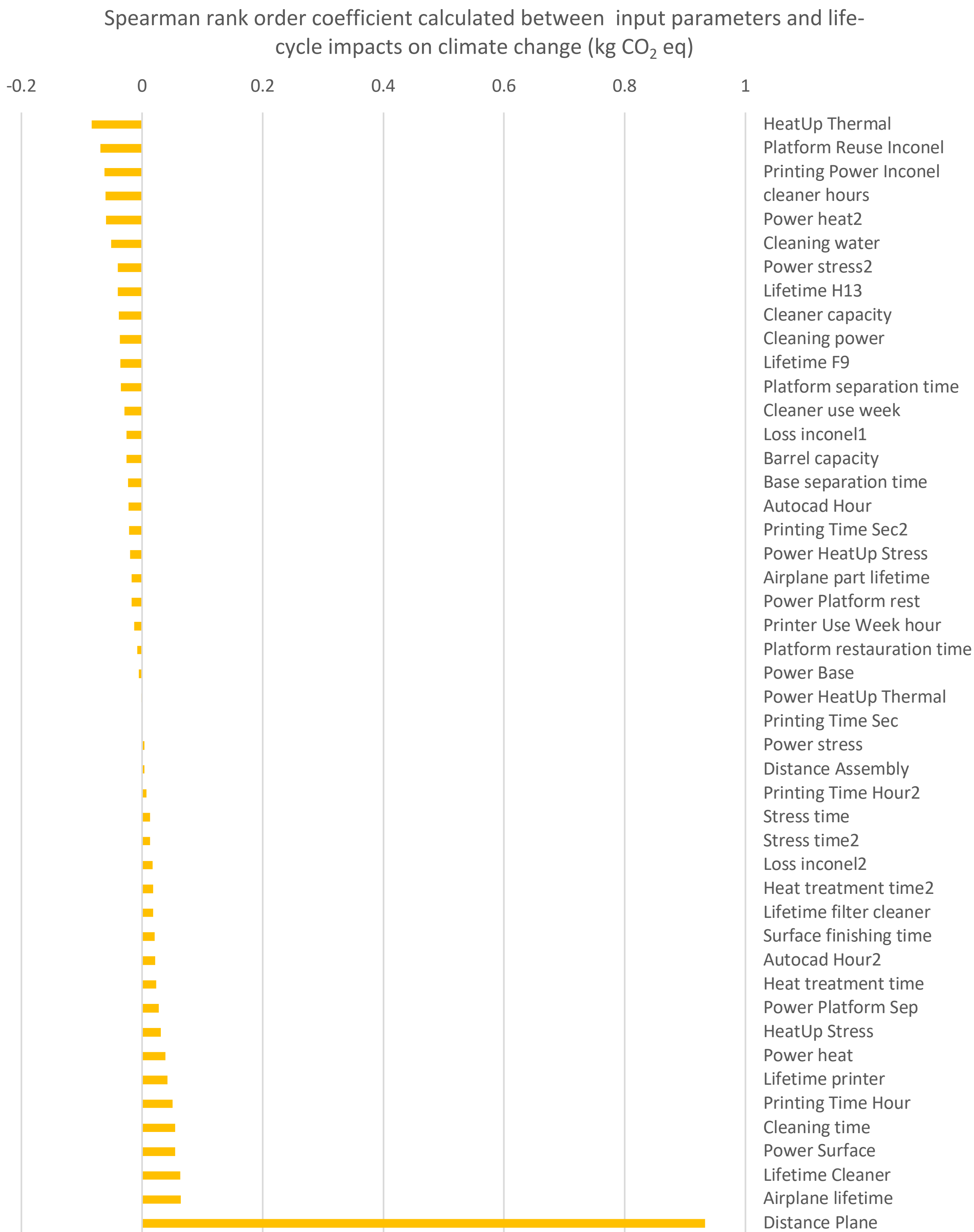


Figure 5.27: Spearman rank order coefficient calculated between input parameters and life-cycle impacts of P3 (AM Optimized)

5.5.1.2.2 Global sensitivity analysis of the life-cycle cost

The GSA performed on the life-cycle cost uncertainty (Figure 5.28) shows that the latter is sensitive to the production cost, the aircraft travelled distance, the fuel consumption and the inflation rate (increasing relationship). However, it is also sensitive to the average part lifetime in the aircraft and the discount rate (at the bottom of the figure) but is illustrated by a decreasing relationship. These parameters should be evaluated and refined in priority in order to reduce life-cycle cost results uncertainty.

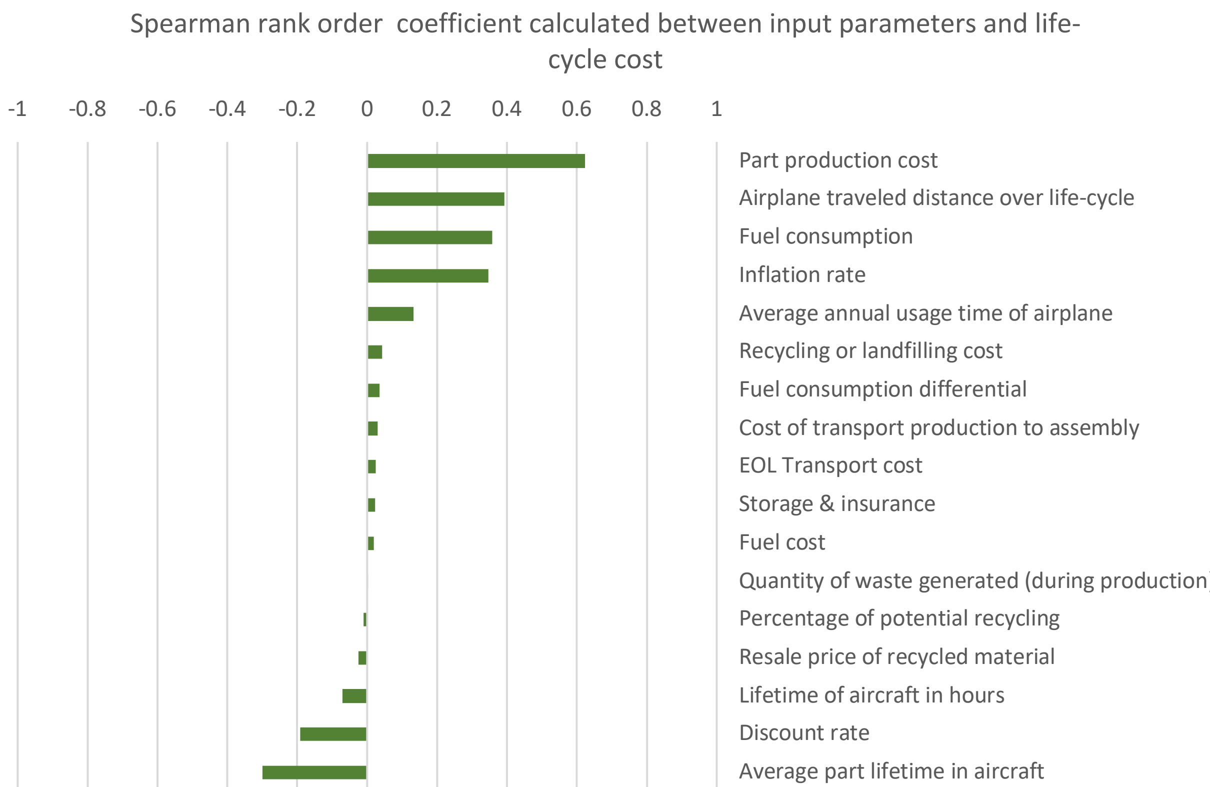


Figure 5.28: Spearman rank order coefficient calculated between input parameters and the life-cycle cost of P3 (AM Optimized)

5.5.1.2.3 Global sensitivity analysis of the production cost

The GSA in Figure 5.29 indicates that the production cost of AM parts is sensitive to the programming time necessary for the post-AM machining operations. It is also the case for the number of mounting templates needed and their cost.

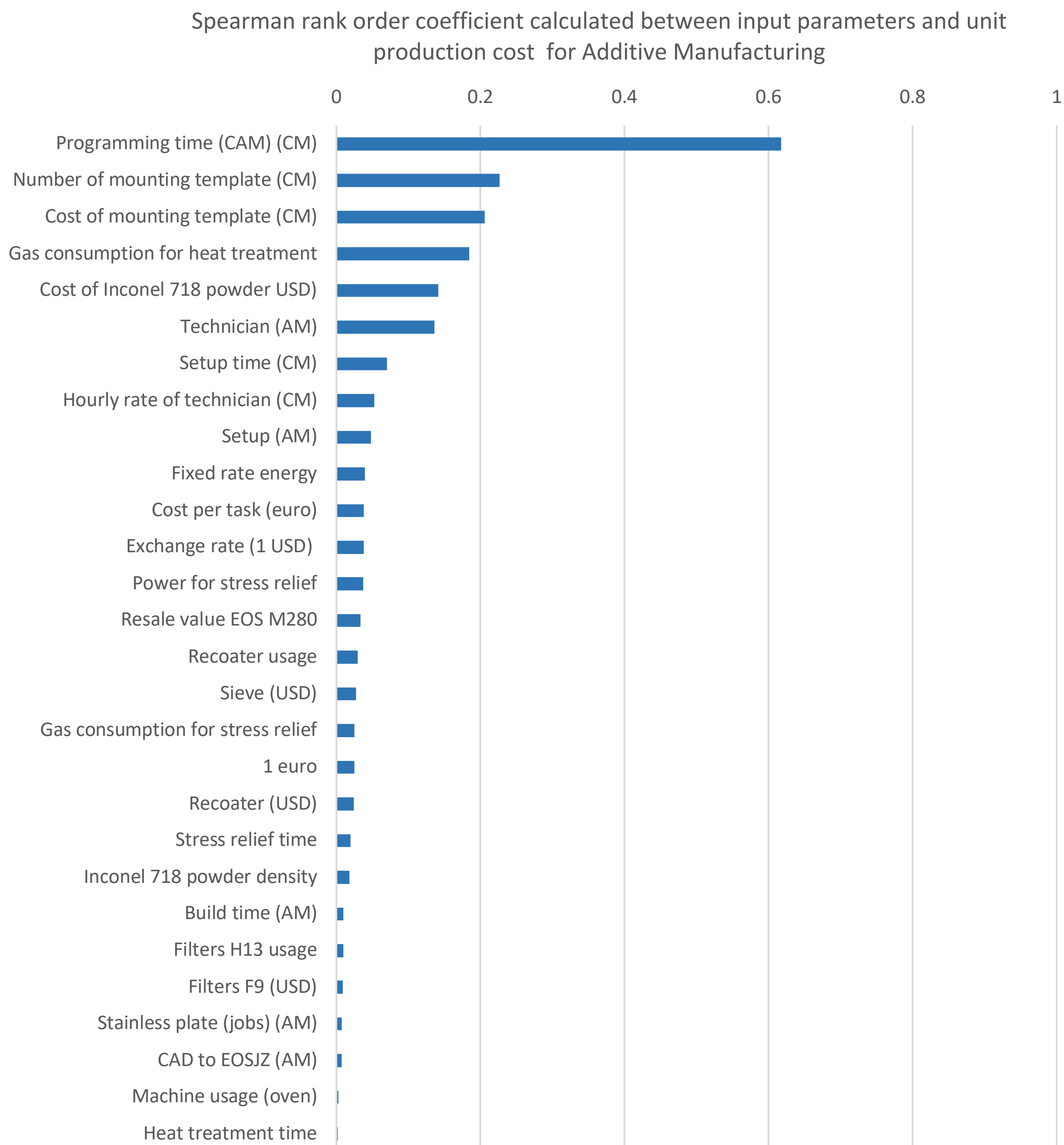


Figure 5.29: Spearman rank order coefficient calculated between input parameters and unit production cost of P3 (AM Optimized)

In addition, Figure 5.30 shows a decreasing relationship between the production cost and the number of components printed by plate (batch size).

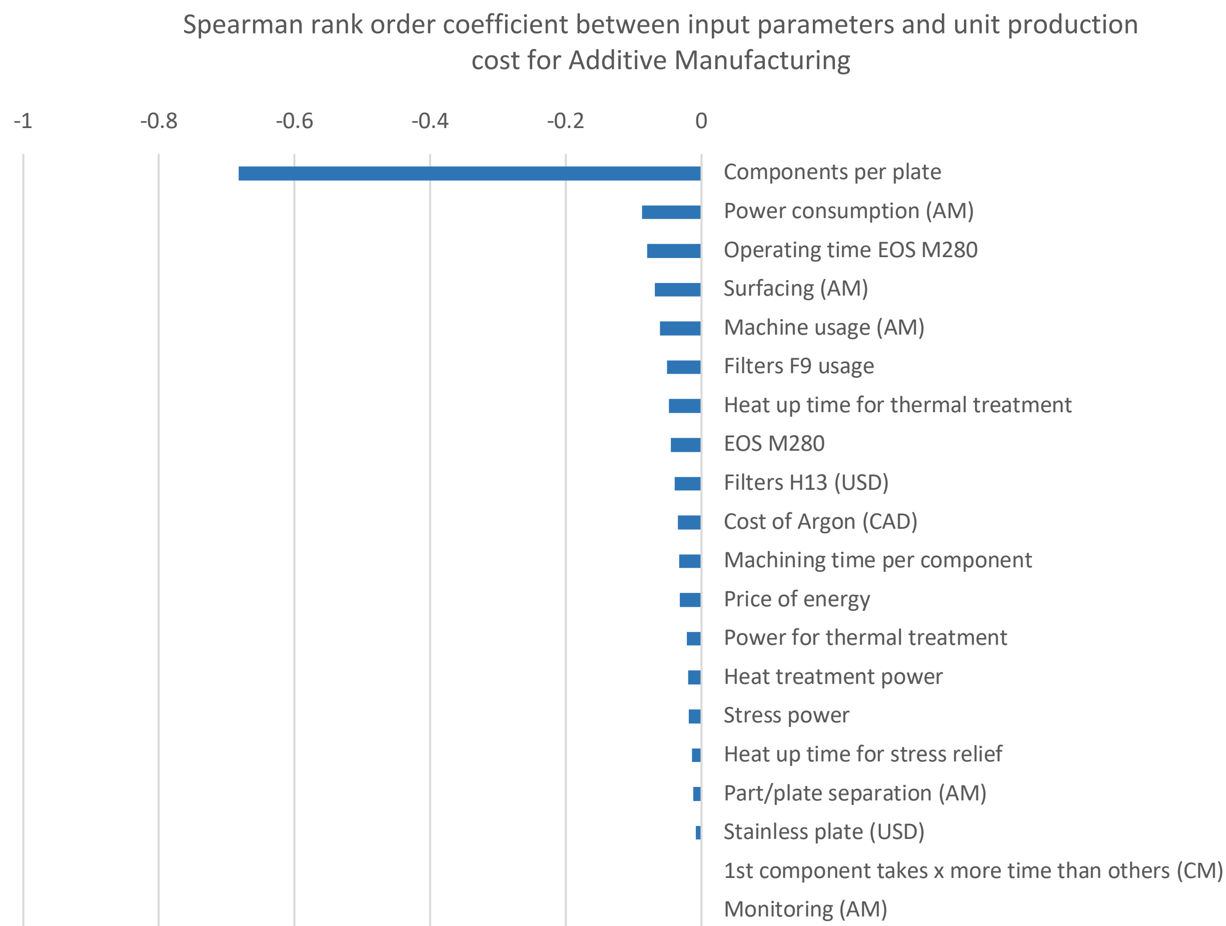


Figure 5.30: Spearman rank order coefficient between input parameters and unit production cost of P3 (AM Optimized)

Finally, Figure 5.31 also shows that the production cost is sensitive to the programming time in CM. It is also the case for the cost of raw material (metal cylinder) and the cost per machining task generated by the Walter online GPS tool (Appendix B).

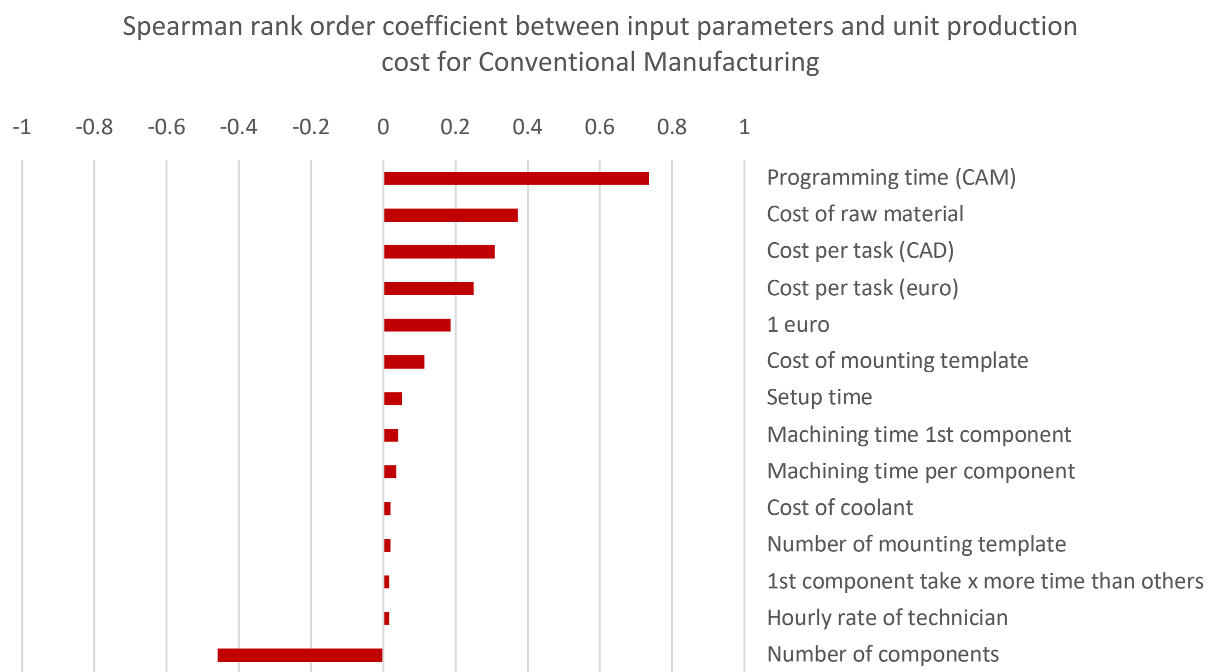


Figure 5.31: Spearman rank order coefficient between input parameters and unit production cost of P1 (CM)

5.5.1.2.4 Global sensitivity analysis of EE

The Spearman rank order coefficient illustrated in Figure 5.32 indicates that the eco-efficiency indicator is sensitive to the life-cycle cost and the trade-off value.

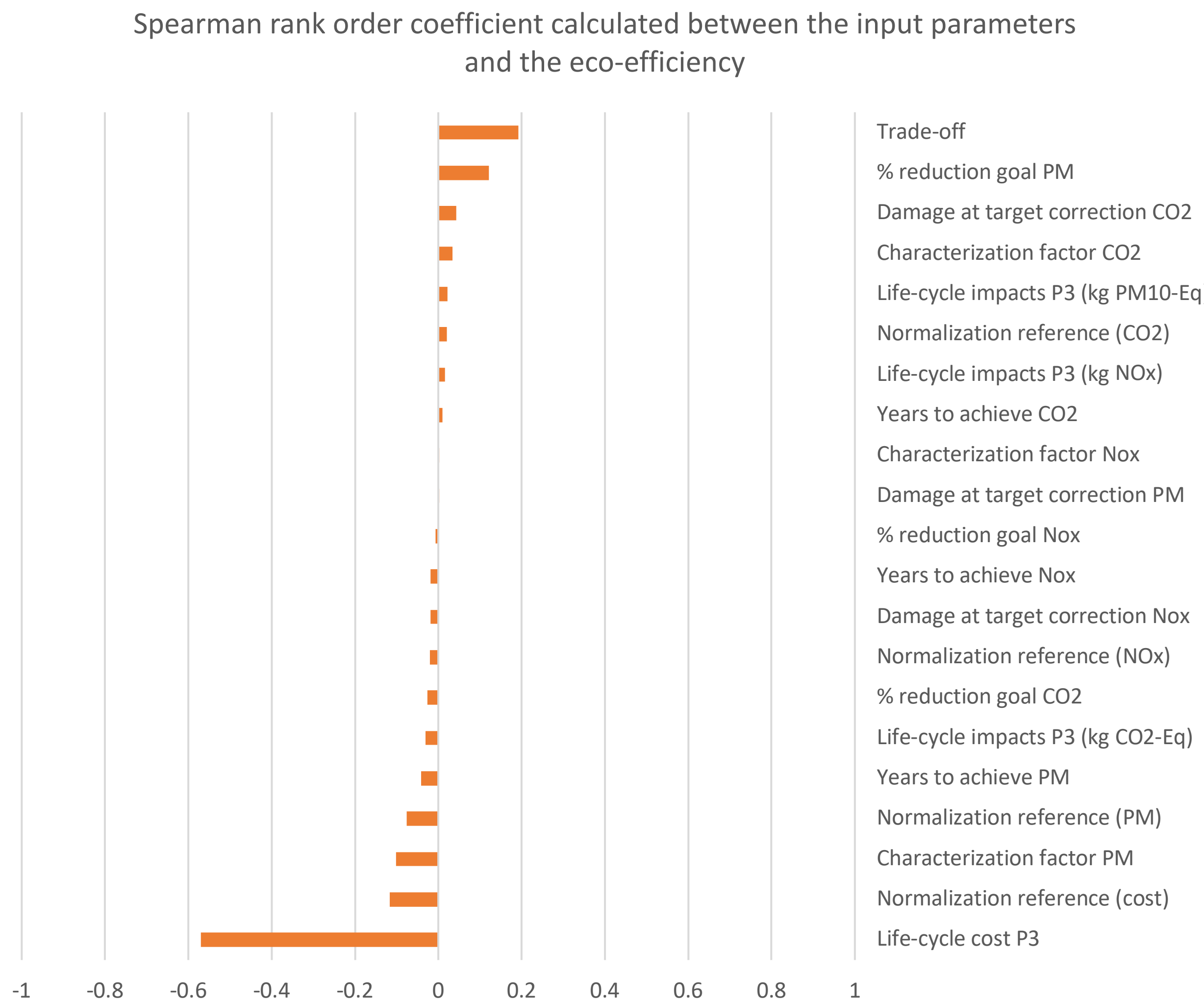


Figure 5.32: Spearman rank order coefficient between input parameters and eco-efficiency of P3 (AM Optimized)

5.6 Case study discussion: main outcomes, strengths and limits

The environmental dimension of eco-efficiency is evaluated using the life-cycle assessment methodology. It is done to compare AM parts to a conventionally manufactured one, all fulfilling the same function. Results show that P3 (AM Optimized) has lower life-cycle environmental impacts than P1 (CM), except for the impacts on ecosystems quality. These are due to some of the AM technology aspects (manufacturing, post-processing, commodities). From a life-cycle perspective, the main advantage of AM is its potential for topology optimization. The latter enables a reduction in fuel consumption during the use phase. Therefore, the part mass is a key parameter of its environmental performance. Now, comparing P2 (AM) and P1 (CM), the main difference between the two is that P2 (AM) helps improving environmental impacts due to the reduced quantities of metal used in the AM process.

The "Easy-LCA" tool developed by Dandres (CIRAIG, 2018) is a valuable tool for supporting the eco-design of AM parts. It allows engineers and designers to yield environmental impacts results in a short time using very basic information about the parts design. The comparative LCA results provided by the study of Dandres (CIRAIG, 2018) and used in this research work could be improved on multiple points.

First, the accuracy of the fuel consumption marginal increase, which is used to calculate the difference in fuel consumption between parts with different weights, should be improved as it is one of the most sensitive parameter. It has been calculated by Dandres (CIRAIG, 2018) for one specific aircraft and would be improved by considering possible variations in different aircraft fleets.

Secondly, the product system of P1 (CM) is not quite equivalent to that of P2 (AM) and P3 (AM Optimized) because there was not enough technical data on machining and equipment. It is modelled using generic data on average metal machining. Increasing the level of detail of this process would help improving the conventional manufacturing results.

In addition to that, the ReCiPe 2008 impact method (Goedkoop et al., 2009) used here to characterize the environmental emissions into midpoints is no longer maintained and has been updated into ReCiPe 2016 (Huijbregts et al., 2017). Since some adaptations and corrections have been made, results generated through ReCiPe 2016 should not be compared to those obtained through ReCiPe 2008 (Huijbregts et al., 2017). Nevertheless, because the aggregated presampled datasets used in the LCA uncertainty analysis were generated through ReCiPe 2008, we choose to stay consistent throughout the impact assessment method of deterministic results. However, it is recommended to generate new deterministic results using ReCiPe 2016, and support them by a stochastic uncertainty assessment using aggregated presamples also generated through this LCIA method.

The LCA assessment results generated for climate change, ecosystems quality, resource consumption and human health show that P3 (AM Optimized) is more environmentally performant than P1 (CM) on all indicators except ecosystems quality. However, this shift in scenarios ranking is not observed using the distance-to-target approach, which considers CO_2, NO_x and PM emissions. The latter approach is used to evaluate the environmental dimension of eco-efficiency, instead of a standard analysis using damage indicators. This is because the number of indicators to interpret for decision-making is reduced. Also, the approach considers emissions which are relevant for the aeronautical sector reduction targets. Nevertheless, it does not account for other emissions potentially contributing to the damages on ecosystems quality. Consequently, it is clear that the environmental indicator choice remains a challenge. The LCA results need to be adapted to the industry. This means they should guide design choices which help reaching reduction targets. However, the LCA method is usually done to account for the complete environmental profile of parts. Therefore, one should consider looking at a wider set of emissions which could potentially be harmful for the environment. It is recommended that a standard eco-efficiency analysis using damage indicators be carried out in parallel to the one using the distance-to-target approach. A comparison of scenarios under uncertainty can help strengthening the decision by indicating the percentage of the time where a damage indicator is compromised.

The life-cycle costing shows that AM with topology optimization enables a reduction in fuel consumption and therefore the use phase cost is lessened. Although benefits are observed during the use phase, it is not always the case when shedding the focus on the production cost. In fact, AM is most performant when multiple parts are printed on the same platform. The batch size has a significant influence on the cost (as well as on environmental impacts and eco-efficiency). Therefore, increasing the batch size assigns the cost responsibility to more than just one part. This being said, the first limit to highlight here is that the main conclusions of the study were drawn for a batch size of 9. This choice was initially made because 9 parts were designed and placed on the build platform when converting the CAD model of the part into a file supported by the AM printer. Nevertheless, the number of parts could have been greater than 9, probably reaching 12 parts on the same platform. This could have possibly decreased the AM cost. In addition to that, the local sensitivity analysis to batch size made for the production cost of CM are based on production volumes of 1, 9 and 90. In reality, much more than 90 parts are usually machined for series production, and in consequence, the cost calculated for 90 parts may have been overestimated.

Another point of discussion is the CM cost calculated using Walter online GPS tool[13]; the cost per machining operation was judged to be good estimation by one of our industrial partners. However, it represents a cost for a part in production (series production) and may not be representative of our case study project scale. Increasing the level of details of the CM process would improve the cost analysis for R&D scale.

Furthermore, in the production cost calculations, the post-processing costs of AM (stress relief, heat treatment) are included. Although data has been extrapolated from real costs encountered in the case study, a more precise and accurate modelling of the gas consumption in function of the volume of the part and time needed to reach the required mechanical properties would improve the production cost results. Although production cost could tend to be higher for AM, the alternative scenarios part designs could change and be adapted specifically in order to put forward the AM technology and reduce the production cost.

One big question which arises through this case study is about the economies of scale. At the product development phase, tests and prototypes are done in order to iteratively improve the design of parts. It is true that the data used in the calculations are based on the laboratory scale. However, they may still be representative of the product and development context. Although an analysis has not been carried out to compare the outcomes in an industrial context, the reality of product development is very close to the one we have attempted to model with the exception of machines impacts and costs which may be in fact allocated to a larger production volume in the R&D department of manufacturing companies. Moreover, the study is limited to the systems boundaries set in the goal and scope definition and the Quebec context. However, different enterprises with

---

[13] https://gps.walter-tools.com/touchtime/walter#/home

different geographical locations might suggest different part design alternatives; accounting for these variations could be done as a sensitivity analysis to evaluate the influence of scenario uncertainty.

Specifically aligned with the aeronautical industry context, the buy-to-fly ratio has been calculated and found to be lower for AM parts than for CM (4:1 versus 20:1). This means that a higher proportion of raw material ends up in the final AM parts than in CM. This engineering metric confirms the environmental results generated through the LCA since it is a good indicator for the scrap produced. It is also a good economic indicator in terms of the cost necessary to treat different waste quantities. Nevertheless, the buy-to-fly ratio has a limited cradle-to-gate scope because it only covers the production stage. Therefore it should not solely be used to claim that one scenario is more environmentally performant than another.

The eco-efficiency results show that the AM optimized part is the most eco-efficient compared to the CM part. In fact, the AM optimized part has a 100 % probability of being more environmentally performant than CM, mostly because of the impacts reduction associated to the use phase. Nevertheless, it has been shown that it is not the case for the life-cycle cost (because of higher production costs depending on the batch size). This underlines the clear existing link between production costs and their direct influence on eco-efficiency results. In fact, this is also confirmed by the GSA, showing that the eco-efficiency is sensitive to the life-cycle cost uncertainty. Therefore refining this data would improve the suggested approach to support decision-making, by decreasing the uncertainty results, and thus increasing the communicated confidence level.

Finally, the probabilistic uncertainty analysis has shown that evaluating the uncertainty in LCA, LCC and EE is important in order to inform on the risk level of decisions. Based on the available data for input parameters, the sampling was based on the uniform distribution, which has the disadvantage of being bounded. Moreover, the variability ranges for these parameters have been defined with the help of the LAMSI for the technical information directly related to the AM process. Nevertheless, providing more information on data uncertainty is useful in order to avoid its overestimation. The Spearman rank order correlation used in the global sensitivity analyses directly depends on the model structure itself, i.e. in the way processes are interrelated and how calculations are made between parameters. It links the input parameter to the outcome, therefore depending on how the model is constructed, some information which could affect the uncertainty may be lost. Others sensitivity methods could be identified in order to better measure the correlation between input parameters and the outcome results (Groen et al., 2017).

5.7 General discussion

One of the main strength of the approach suggested is its relevance to the decision-making context and its easy integration in eco-design tools. The eco-efficiency diagram built on the work of Mami et al. (2017) helps illustrating possible trade-offs between the environmental and economic dimensions in a consistent approach, relevant to the reduction targets set by the aeronautical industry. Nevertheless, these deterministic results do not show the robustness of results and conclusions. Therefore, the underlying risks of the decision are disregarded. By calculating the probabilistic impacts and costs for each scenario and then comparing them under uncertainty, we are able to support the decision by showing the significance of the difference between them. This may also be done for the eco-efficiency indicator. Presenting uncertainty on the eco-efficiency diagram can help decision-makers understand how, depending on their results distributions, there may be cases where the conclusions made on deterministic results are shifted.

Measuring the uncertainty on LCA and LCC distinctly is necessary in order to refine the life-cycle data and reduce the conclusions uncertainty. This can be done through sensitivity analyses. Local sensitivity analyses are deterministic approaches showing the influence of a slight variation in a parameter value while keeping all other parameters value constant. However, they require expert judgement for the choice of parameters. Thus, they are supported here by global sensitivity analyses to consider the complete input parameter set (Borgonovo & Plischke, 2016). The Spearman rank order coefficient used is an example of global sensitivity method which is directly generated from the Monte Carlo simulations. It is is convenient for non-linear models (Altman & Krzywinski, 2015) and can help identifying the main uncertainty contributors, thus, guiding data collection efforts.

The uncertainty approach based on the precalculated aggregated LCA datasets adopted in the approach here is well suited to be implemented in eco-design tools, because of its limited calculation time. However, several limitations apply. It only considers LCI uncertainty, yet there is uncertainty associated to the characterization and normalization factors. One considerable improvement would be to account for the uncertainty in LCIA methods, by presampling characterization factors generated by dependent sampling of common model parameters (Lesage et al., 2018). Furthermore, scenario and model uncertainty are not considered. Because results are also influenced by these two uncertainty sources, it is recommended to quantify them simultaneously with parameter uncertainty (Huijbregts et al., 2003). Distributions must be chosen for each input parameter, thus the results depend on the knowledge about the variability of input parameters modelled. Finally, the choice of correlation coefficient used in the global sensitivity analysis is debatable. In fact, using Spearman when there are too many interactions in the model may yield erroneous results (Saltelli et al., 1999). Because it is based on the rank rather than on raw data, the Spearman rank order coefficient is directly influenced by the model structure.

The biggest challenge left to the decision-maker is to set their accepted uncertainty level (threshold percentage: for example, if A is better than B at least "80%" of the time, then A is chosen over B). In other words, even though the probability of A being better than B is shown, the decision will directly depend on their risk management approach. Increasing the number of Monte Carlo iterations can help improve the confidence given to results.

One of the most important limit associated to an eco-design approach built on eco-efficiency is that the possible trade-offs to be made do not have the same importance over the value chain. For example, the production of AM compared to CM parts may not be encouraged if it does not show direct benefits to the manufacturer. Although this is true, AM parts may add value to the aircraft operator who directly benefits from the fuel reduction during the use phase. This also means that the manufacturer may sell their product at a higher price in order to increase their profits.

As a result of this discussion, an ideal eco-design approach for AM would be a combination of LCA, LCC in an eco-efficiency framework integrating uncertainty. This framework would be a strong asset to AM and engineering design processes in general if an iterative design optimization approach is followed, as the one suggest by Tang et al. (2016). In other words, after each single step of the AM design process, the calculation of the environmental profile would be computed and supported by uncertainty in order to give feedback on the next step to take, while staying aligned with economic choices.

In order to successfully integrate eco-design for AM, a good understanding of the AM design process in needed, because of the multiple technical conditions under which AM performs optimally. In fact, according to Lindemann and Jahnke (2017), “before thinking about parts costs, one needs to address the strategic question of whether the use of additive manufacturing is beneficial for the field of application”. In consequence, it is only if these benefits are clear that the decision-making process should be initiated. A part would be a good candidate for AM if the technical aspects are confirmed at first and if its design offers economic benefits. In addition to that, two major aspects contributing to decision-making are the part geometry and the batch size. In fact, the part geometry indicates the type of optimization required for the part (topology, shape, size), and each optimization type has criteria it must respect. Therefore, performing eco-design should be properly adapted to the AM design process in order to guide eco-efficient choices while respecting technical constraints.

In addition to that, the environmental indicator used may be a challenge for implementing eco-design. Using environmental indicators such as endpoints is a consistent way of representing the complete profile of a scenario in terms of its potential environmental impacts. However, if results show different trends from an indicator to another, it may become more difficult to make a decision. Regardless of the indicator choice, one should keep in mind the risks for the environment that are implied with each decision throughout the eco-design process.

Finally, in order to ensure eco-design for AM is operational, strengthening the links between actors from the AM business ecosystem would be necessary because it would increase collaboration efforts of AM technology induced businesses (Kage, Krüger, & Gausemeier, 2017) towards more eco-efficient products and services.

CONCLUSION AND RECOMMENDATIONS

The general objective of this project was to integrate uncertainty knowledge into an eco-design approach built on the eco-efficiency concept, in order to help industrial partners make informed and robust decisions from a life-cycle perspective. This approach, built around a case study on additive manufacturing, was applied to the aeronautical industry.

The eco-design methodology combines environmental and cost aspects based on the eco-efficiency framework developed by Mami et al (2017). The main contribution of our project is the integration of uncertainty in order to measure the robustness of the results and the transparency of conclusions for a more informed decision-making. The confidence on results is strengthened by communicating the probability of a scenario being better than another one it is compared to. The transparency of conclusions is increased by identifying the parameters influencing the most the results uncertainty. The uncertainty is assessed in parallel to the LCA, LCC and EE results and integrated in an eco-design tool with short computation time.

From the case study, it can be concluded that AM is a promising technology for the aeronautical sector. It improves the environmental, cost and eco-efficiency performances compared to CM. These improvements are mainly due to topology optimization, which shows subsequent benefits in light weighting and reduction of fuel consumed during the use phase. In fact, the probability of AM with topology optimization being better than CM is more significant than without topology optimization.

This research work specifically focused on the potential of eco-design in AM relatively to the design of lightweight structures. Nevertheless, more research should be performed beyond incremental improvement. The AM technology allows to design complex parts, but also to redesign existing parts with potential benefits such as increased material and resource efficiency.

A strong understanding of "Design for Additive Manufacturing" is needed to overcome some of current AM technological challenges such as the need for post-processing, post-AM machining, and the recyclability of the metal powder waste. Our stochastic ecoefficiency based approach provides an opportunity to improve the sustainability of the AM technology and increase its competitiveness compared to conventional methods. Yet, a tool is not enough; eco-design should ideally be applied by AM engineers, or alternatively by LCA practitioners working closely and interactively with the AM engineering team. We explain below how this eco-design approach can be used for communication purposes. Also, some recommendations are formulated in order to support the implementation of the different elements of the stochastic eco-efficiency framework.

The main advantage of the eco-design approach suggested here is that the underlying complexity of uncertainty interpretation is shorted by the way results are communicated. In fact, presenting the probability of a scenario being better than another it is compared to can help supporting the decision-making process. It is recommended to set a threshold value; if the results are above this threshold for a specific design alternative, one could choose this alternative as the most eco-efficient scenario among the others.

How can the eco-design approach be implemented into a decision-making structure? In the AM context, at first, a decision must be made at the mechanical level in order to confirm that the design alternatives respect technical requirements and constraints. Then, a life-cycle cost assessment is suggested to complete the traditional cost analysis usually performed to confirm the economic feasibility of the design alternatives. The scenarios which are compliant with the technical and economic aspects are retained. Afterwards, assessing the potential life-cycle impacts can help identifying "hot spots" and possible improvements as feedback loops early in the design stages. Finally, an eco-efficiency framework can be used to integrate both the cost and environmental dimensions. It helps identifying the most eco-efficient scenarios and eventually possible trade-offs. The uncertainty assessment gives the "go" to executing the decision which puts forward the scenario which has the highest probability of being the most eco-efficient. Additionally, the eco-design approach must align with a well-defined structure. It should translate a shared responsibility throughout the different product development work levels and should be implemented as a decision support system (Poudelet et al., 2012). The first step to do so is to understand the current decision-making process and the actors involved (consumer, engineering team, research and development, etc.). The current decision-making process should be diagnosed in order to evaluate each actor's current activities and analyze ways to account for eco-efficiency as a retrospective tool throughout the process. If a specific stochastic eco-efficiency tool is developed, it should be easy to use by non LCA experts and adapted to meet the needs and day-to-day reality of designers and engineers. It is recommended to continuously update it so that its use is ensured in the future (Poudelet et al., 2012).

BIBLIOGRAPHY

Allwood, J. M., Ashby, M. F., Gutowski, T. G., & Worrell, E. (2011). Material efficiency: A white paper. *Resources, Conservation and Recycling, 55(3),* 362-381. https://doi.org/10.1016/j.resconrec.2010.11.002

Altman, N., & Krzywinski, M. (2015). Points of Significance: Association, correlation and causation. *Nature Methods, 12*(10), 899-900. https://doi.org/10.1038/nmeth.3587

Alton, C. C., & Underwood, P. B. (2003). Let us make impact assessment more accessible. *Environmental Impact Assessment Review, 23(2),* 141-153. https://doi.org/10.1016/S0195-9255(02)00093-8

Ammar, M., Zayed, T., & Moselhi, O. (2012). Fuzzy-based life-cycle cost model for decision making under subjectivity. *Journal of Construction Engineering and Management, 139*(5), 556-563. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000576

Attaran, M. (2017). The rise of 3-D printing: The advantages of additive manufacturing over traditional manufacturing. *Business Horizons, 60*(5), 677-688. https://doi.org/10.1016/j.bushor.2017.05.011

Atzeni, E., Iuliano, L., & Salmi, A. (2011). On the competitiveness of additive manufacturing for the production of metal parts.

Battke, B., Schmidt, T. S., Grosspietsch, D., & Hoffmann, V. H. (2013). A review and probabilistic model of lifecycle costs of stationary batteries in multiple applications. *Renewable and Sustainable Energy Reviews, 25*, 240-250. https://doi.org/10.1016/j.rser.2013.04.023

Baumers, M., Tuck, C., Hague, R., Ashcroft, I., & Wildman, R. (2010). *A comparative study of metallic additive manufacturing power consumption.* Paper presented at the 21st Annual International Solid freeform fabrication symposium.

Bendsøe, M. P., & Sigmund, O. (2004). *Topology optimization: theory, methods, and applications* https://doi.org/10.1007/978-3-662-05086-6

Bhamra, T., Evans, S., McAloone, T. C., Simon, M., Poole, S., & Sweatman, A. (1999). *Integrating environmental decisions into the product development process. I. The early stages.* Paper presented at the Proceedings First International Symposium on Environmentally Conscious Design and Inverse Manufacturing. http://doi.org/10.1109/ECODIM.1999.747633

Bhander, G. S., Hauschild, M., & McAloone, T. (2003). Implementing life cycle assessment in product development. *Environmental Progress & Sustainable Energy, 22*(4), 255-267. https://doi.org/10.1002/ep.670220414

Björklund, A. E. (2002). Survey of Approaches to Improve Reliability in LCA. *The International Journal of Life Cycle ssessment, 7*(2), 64-72. http://doi.org/10.1065/Ica2001.12.071

Bjørn, A., & Hauschild, M. Z. (2013). Absolute versus Relative Environmental Sustainability: What can the Cradle-to-Cradle and Eco-efficiency Concepts Learn from Each Other? *Journal of Industrial Ecology, 17*(2), 321-332. https://doi.org/10.1111/j.1530-9290.2012.00520.x

Bombardier. (2016). *Environmental Product Declaration - Bombardier CS100*. Retrieved from http://www.bombardier.com/en/media/newsList/details.bombardier-cs100-aircraft-receives-the-first-environmental-produ0.bombardiercom.html

Borgonovo, E., & Plischke, E. (2016). Sensitivity analysis: A review of recent advances. *European Journal of Operational Research, 248*(3), 869–887. http://doi.org/10.1016/j.ejor.2015.06.032

Boussabaine, A., & Kirkham, R. (2008). *Whole life-cycle costing: risk and risk responses*: John Wiley & Sons.

Bovea, M., & Pérez-Belis, V. (2012). A taxonomy of ecodesign tools for integrating environmental requirements into the product design process. *Journal of Cleaner Production, 20*(1), 61-71. https://doi.org/10.1016/j.jclepro.2011.07.012

Brandão, M., Clift, R., Cowie, A., & Greenhalgh, S. (2014). The Use of Life Cycle Assessment in the Support of Robust (Climate) Policy Making: Comment on "Using Attributional Life Cycle Assessment to Estimate Climate-Change Mitigation." *Journal of Industrial Ecol ogy, 18*(3), 461–463. http://doi.org/10.1111/jiec.12152

Brandt, M. (2016). *Laser Additive Manufacturing: Materials, Design, Technologies, and Applications*: Elsevier Science.

Brezet, H., & Van Hemel, C. (1997). *Ecodesign : A promising approach to sustainable production and consumption.* United Nations Environmental Programme (UNEP).

Broadbent, C., Stevenson, M., Caldiera-Pires, A., Cockburn, D., Lesage, P., Martchek, K., . . . Frischknecht, R. (2011). Aggregated data development. *Global guidance principles for life cycle assessment databases—a basis for greener processes and products. G. Sonnemann and B. Vigon. Shonan, Japan, UNEP-SETAC Life Cycle Initiative*, 67-83.

Budnitz, R. J., Apostolakis, G., & Boore, D. M. (1997). *Recommendations for probabilistic seismic hazard analysis: guidance on uncertainty and use of experts*. Retrieved from http://doi.org/10.2172/479072

Bulle, C., Margni, M., Patouillard, L., Boulay, A.-M., Bourgault, G., De Bruille, V., . . . Humbert, S. (2018). IMPACT World+: a globally regionalized life cycle impact assessment method. *The international journal of life cycle assessment*, 1-22. https://doi.org/10.1007/s11367-019-01583-0

Burkhart, M., & Aurich, J. C. (2015). Framework to predict the environmental impact of additive manufacturing in the life cycle of a commercial vehicle. *Procedia CIRP, 29*, 408-413. https://doi.org/10.1016/j.procir.2015.02.194

CIRAIG. (2018). *Manu-710 Project: Technical report prepared for CRIAQ/CARIC - Sustainability & Life-cycle assessment of aircraft parts made by additive and conventional manufacturing.*

Corrotherm, I. (2018). Can you recycle nickel alloys? Retrieved from https://www.corrotherm.co.uk/blog/can-you-recycle-nickel-alloys

De Koning, A., Schowanek, D., Dewaele, J., Weisbrod, A., & Guinée, J. (2010). Uncertainties in a carbon footprint model for detergents; quantifying the confidence in a comparative result. *The international journal of life cycle assessment, 15*(1), 79. http://doi.org/10.1007/s11367-009-0123-3

Défense nationale et forces armées canadiennes (2014). *Capacité de la prochaine génération de chasseurs, Mise à jour annuelle*. Retrieved from http://www.forces.gc.ca/fr/a-propos-rapports-pubs/prochaine-generation-chasseurs-maj-annuelle-2014.page

DIN, E. (2004). 60300-3-3 Dependability management–Part 3-3: Application guide–Life cycle costing. In: German version EN.

Direct Manufacturing Research Centre (DMRC). (2015). *Annual Report*. Retrieved from http://www.uni-paderborn.de/fileadmin/dmrc/04_DMRC/04_AnnualReport/dmrc_report_2015.pdf

Dornfeld, D. (2010). Green Manufacturing: Degrees of Perfection. Retrieved from http://green-manufacturing.blogspot.com/2010/07/degrees-of-perfection.html.

Ehrlenspiel, K., Kiewert, A., & Lindemann, U. (1998). Kostengünstig entwickeln und konstruieren. *Kostenmanagement bei der integrierten Produktentwicklung, 6*. https://doi.org/10.1007/978-3-540-74223-4

European Commission. (2015). *Reducing emissions from aviation*. European Commission Retrieved from https://ec.europa.eu/clima/policies/transport/aviation_en.

Faludi, J., Bayley, C., Bhogal, S., & Iribarne, M. (2015). Comparing environmental impacts of additive manufacturing vs traditional machining via life-cycle assessment. *Rapid Prototyping Journal, 21*(1), 14-33. https://doi.org/10.1108/RPJ-07-2013-0067

Fugère, M. (2009). *Intégration des critères de conception et de l'analyse de cycle de vie simplifiée pour l'écoconception de produits à usage unique.* (Mémoire de maîtrise, École Polytechnique de Montréal, Montréal, QC). Retrieved from https://publications.polymtl.ca/195

Gebbe, C., Hilmer, S., Götz, G., Lutter-Günther, M., Chen, Q., Unterberger, E., . . . Kamps, T. (2015). Concept of the Green Factory Bavaria in Augsburg. *Procedia CIRP, 32*, 53-57. https://doi.org/10.1016/j.procir.2015.02.214

Gebler, M., Uiterkamp, A. J. S., & Visser, C. (2014). A global sustainability perspective on 3D printing technologies. *Energy Policy, 74*, 158-167. https://doi.org/10.1016/j.enpol.2014.08.033

Gibson, I., Rosen, D. W., & Stucker, B. (2010). *Additive manufacturing technologies.* Boston, MA:Springer. https://doi.org/10.1007/978-1-4419-1120-9

Glade, M. (2005). *Modélisation des coûts de cycle de vie: prévision des coûts de maintenance et de la fiabilité: Application à l'aéronautique.* (Thesis, Ecole centrale de Lyon, Lyon, France). Retrieved from : https://bibli.ec-lyon.fr/exl-doc/mglade.pdf

Gluch, P., & Baumann, H. (2004). The life cycle costing (LCC) approach: a conceptual discussion of its usefulness for environmental decision-making. *Building and environment, 39*(5), 571-580. https://doi.org/10.1016/j.buildenv.2003.10.008

Goedkoop, M., Heijungs, R., Huijbregts, M., De Schryver, A., Struijs, J., & Van Zelm, R. (2009). ReCiPe 2008. *A life cycle impact assessment method which comprises harmonised category indicators at the midpoint and the endpoint level, 1*. Retrieved from : https://www.rivm.nl/en/life-cycle-assessment-lca/recipe

Goedkoop, M., & Spriensma, R. (1995). *The eco-indicator 95*: PRé Consultants Amersfoort.

Graedel, T., & Allenby, B. (1995). Industrial ecology.

Graedel, T. E. (1998). *Streamlined life-cycle assessment*. Upper Saddle River, NJ:Prentice Hall.

Gregory, J., Noshadravan, A., Swei, O., Xu, X., & Kirchain, R. (2017). The importance of incorporating uncertainty into pavement life cycle cost and environmental impact analyses. In *Pavement Life-Cycle Assessment* (pp. 131-142): CRC Press.

Groen, E. A., Bokkers, E. A., Heijungs, R., & de Boer, I. J. (2017). Methods for global sensitivity analysis in life cycle assessment. *The international journal of life cycle assessment, 22*(7), 1125-1137. http://doi.org/10.1007/s11367-016-1217-3

Haggerty, A. C. (2004). *Lifecycle Considerations*. Massachusetts Institute of Technology [Powerpoint presentation]. Retrived from : https://ocw.mit.edu/courses/aeronautics-and-astronautics/16-885j-aircraft-systems-engineering-fall-2004/lecture-notes/lifecycle.pdf

Heijungs, R., & Huijbregts, M. A. (2004). A review of approaches to treat uncertainty in LCA. iEMSs 2004 International Congress, 8. http://doi.org/http://www.iemss.org/iemss2004/pdf/lca/heijarev.pdf

Holshouser, C., Newell, C., Palas, S., Love, L. J., Kunc, V., Lind, R. F., . . . Duty, C. E. (2013). Out of bounds additive manufacturing. *Advanced Materials and Processes, 171*(3).

Hopkinson, N., & Dicknes, P. (2003). Analysis of rapid manufacturing—using layer manufacturing processes for production. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, 217*(1), 31-39. https://doi.org/10.1243/095440603762554596

Huang, R., Riddle, M., Graziano, D., Warren, J., Das, S., Nimbalkar, S., . . . Masanet, E. (2016). Energy and emissions saving potential of additive manufacturing: the case of lightweight aircraft components. *Journal of Cleaner Production, 135*, 1559-1570. https://doi.org/10.1016/j.jclepro.2015.04.109

Huijbregts, M. A., Gilijamse, W., Ragas, A. M., & Reijnders, L. (2003). Evaluating uncertainty in environmental life-cycle assessment. A case study comparing two insulation options for a Dutch one-family dwelling. *Environmental science & technology, 37*(11), 2600-2608. https://doi.org/10.1021/es020971+

Huijbregts, M. A. J. (1998). Application of uncertainty and variability in LCA. *The international journal of life cycle assessment, 3*(5), 273. https://doi.org/10.1007/bf02979835

Huijbregts, M. A. J., Steinmann, Z. J. N., Elshout, P. M. F., Stam, G., Verones, F., Vieira, M., . . . van Zelm, R. (2017). ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. *The international journal of life cycle assessment, 22*(2), 138-147. https://doi.org/10.1007/s11367-016-1246-y

Hunkeler, D., Lichtenvort, K., & Rebitzer, G. (2008b). *Environmental life cycle costing* (1st Edition). Boca Raton, FL:CRC Press. https://doi.org/10.1201/9781420054736

Hunkeler, D., & Rebitzer, G. (2003). Life Cycle costing—paving the road to sustainable development? *The international journal of life cycle assessment, 8*(2), 109-110. https://doi.org/10.1007/BF02978435

Huppes, G., & Ishikawa, M. (2005b). A Framework for Quantified Eco-efficiency Analysis. *Journal of Industrial Ecology, 9*(4), 25-41. https://doi.org/10.1162/108819805775247882

Huppes, G., & Ishikawa, M. (2007). An introduction to quantified eco-efficiency analysis. In *Quantified Eco-Efficiency*. https://doi.org/10.1007/1-4020-5399-1_1

Huppes, G., van Rooijen, M., Kleijn, R., Heijungs, R., de Koning, A., & van Oers, L. (2004). Life cycle costing and the environment. *Report of a project commissioned by the Ministry of VROM-DGM for the RIVM Expertise Centre LCA*.

International Air Transport Association (IATA). (2013). Roadmap 2050. Retrieved from https://www.iata.org/whatwedo/environment/Documents/technology-roadmap-2013.pdf

International Civil Aviation Organization. (2017). Uniting Aviation: A United Nations Specialized Agency. Retrieved from https://www.icao.int/Newsroom/Pages/ICAO-Council-adopts-new-CO2-emissions-standard-for-aircraft.aspx

International Energy Agency. (2010). *World Energy Outlook*. Retrieved from https://www.iea.org/weo/

International Organization for Standardization (ISO). (2015). ISO14001:2015 Environmental management - Requirements with guidance for use.

International Organization for Standardization (ISO). (2006a). ISO14040:2006 Environmental management-Life cycle assessment-Principles and framework.

International Organization for Standardization (ISO). (2006b). ISO14044:2006 Environmental management - Life cycle assessment - Requirements and guidelines.

International Organization for Standardization (ISO). (2012). ISO14045:2012 Environmental management-Eco-efficiency assessment of product systems-Principles, requirements and guidelines.

International Organization for Standardization (ISO) /ASTM. (2015). Standard Terminology for Additive Manufacturing.

International Organization for Standardization (ISO). (2002). ISO/TR 14062:2002 Environmental management. Integrating environmental ascpects into product design and development.

Ilg, P., Scope, C., Muench, S., & Guenther, E. (2017). Uncertainty in life cycle costing for long-range infrastructure. Part I: leveling the playing field to address uncertainties. *The international journal of life cycle assessment, 22*(2), 277-292. https://doi.org/10.1007/s11367-016-1154-1

J.O'Hare, E.Cope, & Warde, S. (2015). *Five steps to eco design - Improving the environmental performance of products through design*. Retrieved from https://downloadfiles.grantadesign.com/pdf/FiveStepsToEcoDesign.pdf

Jolliet, O., Margni, M., Charles, R., Humbert, S., Payet, J., Rebitzer, G., & Rosenbaum, R. (2003). IMPACT 2002+: A new life cycle impact assessment methodology. *The international journal of life cycle assessment, 8*(6), 324. doi:10.1007/bf02978505

Jolliet, O., Müller-Wenk, R., Bare, J., Brent, A., Goedkoop, M., Heijungs, R., . . . Potting, J. (2004). The LCIA midpoint-damage framework of the UNEP/SETAC life cycle initiative. *The international journal of life cycle assessment, 9*(6), 394. https://doi.org/10.1007/BF02979083

Jolliet, O., Saadé, M., & Crettaz, P. (2010). *Analyse du cycle de vie: comprendre et réaliser un écobilan* (Vol. 23): PPUR Presses polytechniques.

Jolliet, O., Saade-Sbeih, M., Shaked, S., Jolliet, A., & Crettaz, P. (2015). *Environmental Life Cycle Assessment*. Boca Raton, UNITED STATES: CRC Press.

Kage, M., Krüger, C., & Gausemeier, J. (2017). *Positioning in technology-induced Business Ecosystems like Additive Manufacturing.* Paper presented at the ISPIM Innovation Symposium.

Kägi, T., Dinkel, F., Frischknecht, R., Humbert, S., Lindberg, J., De Mester, S., . . . Schenker, U. W. (2016). Session "Midpoint, endpoint or single score for decision-making?"—SETAC Europe 25th Annual Meeting, May 5th, 2015. *The international journal of life cycle assessment, 21*(1), 129-132. https://doi.org/10.1007/s11367-015-0998-0

Khan, K. A., & Houston, G. D. (2000). *Design optimization using life cycle cost analysis for low operating costs*. Retrieved from https://apps.dtic.mil/dtic/tr/fulltext/u2/p010423.pdf

Kianian, B., & Larsson, T. C. (2015). *Additive manufacturing technology potential: a cleaner manufacturing alternative.* Paper presented at the 20th design for manufacturing and the life cycle conference (DFMLC). Proceedings of the ASME 2015 international design engineering technical conferences & computers and information in engineering conference (IDETC/CIE 2015). doi:10.1115/DETC2015-46075

Kloepffer, W. (2008). Life cycle sustainability assessment of products. *The international journal of life cycle assessment, 13*(2), 89. doi:10.1065/lca2008.02.376

Klöpffer, W. (2003). Life-cycle based methods for sustainable product development. https://doi.org/10.1007/BF02978462

Knight, P., & Jenkins, J. O. (2009). Adopting and applying eco-design techniques: a practitioners perspective. *Journal of Cleaner Production, 17*(5), 549-558. https://doi.org/10.1016/j.jclepro.2008.10.002

Krzywinski, M., & Altman, N. (2013). Points of significance: Importance of being uncertain. In: Nature Publishing Group. https://doi.org/10.1038/nmeth.2613

Kuosmanen, T. (2005). Measurement and analysis of eco-efficiency: An economist's perspective. *Journal of Industrial Ecology, 9*(4), 15-18. https://doi.org/10.1162/108819805775248025

Le Pochat, S. (2005). *Ecodesign integration in SMES-proposal for a know-how appropriation method for environmental product design.* Arts et Métiers ParisTech.

Lesage, P., Mutel, C., Schenker, U., & Margni, M. (2018). Uncertainty analysis in LCA using precalculated aggregated datasets. *The international journal of life cycle assessment, 23*(11), 2248-2265. https://doi.org/10.1007/s11367-018-1444-x

Lewandowska, A., & Kurczewski, P. (2010). ISO 14062 in theory and practice—ecodesign procedure. Part 1: structure and theory. *The international journal of life cycle assessment, 15*(8), 769-776. https://doi.org/10.1007/s11367-010-0228-8

Li, Y., Chen, J., & Feng, L. (2013). Dealing with uncertainty: A survey of theories and practices. *IEEE Transactions on Knowledge and Data Engineering, 25*(11), 2463-2482. http://doi.org/10.1109/TKDE.2012.179

Lindemann, C., Jahnke, U., Moi, M., & Koch, R. (2012). *Analyzing product lifecycle costs for a better understanding of cost drivers in additive manufacturing.* Paper presented at the 23th Annual International Solid Freeform Fabrication Symposium–An Additive Manufacturing Conference. Austin Texas USA 6th-8th August.

Lindemann, C., Jahnke, U., Moi, M., & Koch, R. (2013). *Impact and influence factors of additive manufacturing on product lifecycle costs.* Paper presented at the Proceedings of the Solid Freeform Fabrication Symposium.

Lindemann, C. F. W., & Jahnke, U. (2017). Modelling of laser additive manufactured product lifecycle costs. *Laser Additive Manufacturing*. https://doi.org/10.1016/B978-0-08-100433-3.00011-7

Mahamood, R. M., Shukla, M., & Pityana, S. (2014). Laser Additive Manufacturing in Surface Modification of Metals. *Surface Engineering Techniques and Applications: Research Advancements*, 222-248.

Malshe, H., Nagarajan, H., Pan, Y., & Haapala, K. (2015). *Profile of sustainability in additive manufacturing and environmental assessment of a novel stereolithography process.* Paper presented at the ASME 2015 International Manufacturing Science and Engineering Conference.

Mami, F., Revéret, J.-P., Fallaha, S., & Margni, M. (2017). Evaluating Eco-Efficiency of 3D Printing in the Aeronautic Industry. *Journal of Industrial Ecology, 21*(S1), S37-S48. https://doi.org/10.1111/jiec.12693

Mattila, T., Kujanpää, M., Dahlbo, H., Soukka, R., & Myllymaa, T. (2011). Uncertainty and sensitivity in the carbon footprint of shopping bags. *Journal of Industrial Ecology, 15*(2), 217-227. https://doi.org/10.1111/j.1530-9290.2010.00326.x

Millet, D., Bistagnino, L., Lanzavecchia, C., Camous, R., & Poldma, T. (2007). Does the potential of the use of LCA match the design team needs? *Journal of Cleaner Production, 15*(4), 335-346. https://doi.org/10.1016/j.jclepro.2005.07.016

Minitab. (2017). A comparison of the Pearson and Spearman correlation methods. Retrieved from https://support.minitab.com/en-us/minitab-express/1/help-and-how-to/modeling-statistics/regression/supporting-topics/basics/a-comparison-of-the-pearson-and-spearman-correlation-methods/

Mognol, P., Lepicart, D., & Perry, N. (2006). Rapid prototyping: energy and environment in the spotlight. *Rapid Prototyping Journal, 12*(1), 26-34. https://doi.org/10.1108/13552540610637246

Morin, E. (2017). L'avenir de la décision : connaître et agir en complexité - ESSEC Business School | Coursera. Retrieved March 6, 2018, from https://www.coursera.org/learn/lavenir-de-la-decision/home/info

Morrow, W., Qi, H., Kim, I., Mazumder, J., & Skerlos, S. (2007). Environmental aspects of laser-based and conventional tool and die manufacturing. *Journal of Cleaner Production, 15*(10), 932-943. https://doi.org/10.1016/j.jclepro.2005.11.030

Mota, C., Puppi, D., Chiellini, F., & Chiellini, E. (2015). Additive manufacturing techniques for the production of tissue engineering constructs. *Journal of tissue engineering and regenerative medicine, 9*(3), 174-190. https://doi.org/10.1002/term.1635

Oak Ridge National Laboratory (ORNL). (2010). *Aerospace Workshop Planning Session Summary Report. Retrieved from :https://web.ornl.gov/sci/manufacturing/docs/Aerospace_Workshop_Report.pdf*

Pahl, G., Beitz, W., Feldhusen, J., & Grote, K. H. (2006). *Engineering Design: A Systematic Approach*: Springer London.

Paris, H., Mokhtarian, H., Coatanéa, E., Museau, M., & Ituarte, I. F. (2016). Comparative environmental impacts of additive and subtractive manufacturing technologies. *CIRP Annals-Manufacturing Technology, 65*(1), 29-32. https://doi.org/10.1016/j.cirp.2016.04.036

Patouillard, L. (2018). *Régionalisation en analyse du cycle de vie: Analyse conséquentielle des filières alternatives pour le transport en france.* (Thesis, Polytechnique Montréal, Montreal, Quebec). Retrieved from https://publications.polymtl.ca/3106/1/2018_LaurePatouillard.pdf

Pinkerton, A. J. (2016). Lasers in additive manufacturing. *Optics & Laser Technology, 78*, 25-32. http://dx.doi.org/10.1016/j.optlastec.2015.09.025

Poudelet, V., Chayer, J.-A., Margni, M., Pellerin, R., & Samson, R. (2012). A process-based approach to operationalize life cycle assessment through the development of an eco-design decision-support system. *Journal of Cleaner Production, 33*, 192-201. https://doi.org/10.1016/j.jclepro.2012.04.005

Rebitzer, G. (2002). Integrating life cycle costing and life cycle assessment for managing costs and environmental impacts in supply chains. *Cost management in supply chains* (pp. 127-146). https://doi.org/10.1007/978-3-662-11377-6_8

Reeves, P., & Mendis, D. (2015). The current status and impact of 3D printing within the industrial sector: an analysis of six case studies. Retrieved from: http://eprints.bournemouth.ac.uk/21873/1/The_Current_Status_and_Impact_of_3D_Printing_Within_the_Industrial_Sector_-_Study_II.pdf

Refsgaard, J. C., van der Sluijs, J. P., Højberg, A. L., & Vanrolleghem, P. A. (2007). Uncertainty in the environmental modelling process–a framework and guidance. *Environmental modelling & software, 22*(11), 1543-1556. http://doi.org/10.1016/j.envsoft.2007.02.004

Reiher, T., Lindemann, C., Jahnke, U., Deppe, G., & Koch, R. (2017). Holistic approach for industrializing AM technology: from part selection to test and verification. *Progress in Additive Manufacturing, 2*(1-2), 43-55. https://doi.org/10.1007/s40964-017-0018-y

Réseau-Québec-3D. (2016). *Fabrication additive au Québec: Rapport sur les travaux des comités consultatifs du réseau Québec 3D. Constats et perspectives*.

Rossi, M., Germani, M., & Zamagni, A. (2016). Review of ecodesign methods and tools. Barriers and strategies for an effective implementation in industrial companies. *Journal of Cleaner Production, 129* (Supplement C), 361-373. https://doi.org/10.1016/j.jclepro.2016.04.051

Ruffo, M., & Hague, R. (2007). Cost estimation for rapid manufacturing'simultaneous production of mixed components using laser sintering. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 221*(11), 1585-1591. https://doi.org/10.1243/09544054JEM894

Ruffo, M., Tuck, C., & Hague, R. (2006). Cost estimation for rapid manufacturing-laser sintering production for low to medium volumes. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 220*(9), 1417-1427. https://doi.org/10.1243/09544054JEM517

Saltelli, A., Tarantola, S., & Chan, K.-S. (1999). A quantitative model-independent method for global sensitivity analysis of model output. *Technometrics, 41*(1), 39-56. https://doi.org/10.1080/00401706.1999.10485594

Scaravetti, D., Nadeau, J.-P., Pailhes, J., & Sebastian, P. (2005). Structuring of embodiment design problem based on the product lifecycle. *International Journal of Product Development, 2*(1-2), 47-70.

Schmidheiny, S. (1992). *Changing course: A global business perspective on development and the environment* (Vol. 1): MIT press.

Schmidt, W.-P. (2003). Life cycle costing as part of design for environment environmental business cases. *The international journal of life cycle assessment, 8*(3), 167. https://doi.org/10.1007/BF02978464

Serres, N., Tidu, D., Sankare, S., & Hlawka, F. (2011). Environmental comparison of MESO-CLAD process and conventional machining implementing life cycle assessment. *Journal of Cleaner Production, 19*(9), 1117-1124. https://doi.org/10.1016/j.jclepro.2010.12.010

Steinmann, Z. J. N., Hauck, M., Karuppiah, R., Laurenzi, I. J., & Huijbregts, M. A. J. (2014). A methodology for separating uncertainty and variability in the life cycle greenhouse gas emissions of coal-fueled power generation in the USA. *The international journal of life cycle assessment, 19*(5), 1146-1155. https://doi.org/10.1007/s11367-014-0717-2

Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., . . . Midgley, B. (2013). IPCC, 2013: climate change 2013: the physical science basis. Contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change. In: Cambridge University Press. https://doi.org/10.1017/CBO9781107415324

Swei, O., Gregory, J., & Kirchain, R. (2016). Probabilistic approach for long-run price projections: Case study of concrete and asphalt. *Journal of Construction Engineering and Management, 143*(1). https://doi.org/10.3141/2523-06

Tang, Y., Mak, K., & Zhao, Y. F. (2016). A framework to reduce product environmental impact through design optimization for additive manufacturing. *Journal of Cleaner Production, 137*, 1560-1572. https://doi.org/10.1016/j.jclepro.2016.06.037

Thompson, M. (2018). *Cultural theory*.https://doi.org/10.4324/9780429501180

Timercan, A. (2017). Production cost estimation - Excel calculator - Laboratoire sur les alliages à mémoire et systèmes intelligents (LAMSI).

Weidema, B. P. (2009). Avoiding or Ignoring Uncertainty. *Journal of Industrial Ecology, 13*(3), 354-356. https://doi.org/10.1111/j.1530-9290.2009.00132.x

Weidema, B. P., & Wesnaes, M. S. (1996). Data quality management for life cycle inventories—an example of using data quality indicators. *Journal of Cleaner Production, 4*(3-4), 167-174. https://doi.org/10.1016/S0959-6526(96)00043-1

Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., Weidema, B. (2016). The ecoinvent database version 3 (part I): overview and methodology. *The International Journal of Life Cycle Assessment*. https://doi.org/10.1007/s11367-016-1087-8

Willcox, K. (2004). Aircraft systems engineering: cost analysis. Retrieved from https://ocw.mit.edu/courses/aeronautics-and-astronautics/16-885j-aircraft-systems-engineering-fall-2004/lecture-notes/pres_willcox.pdf

Wohlers associates Inc. (2014). Wohlers report. Retrieved from: https://wohlersassociates.com/2014-ExSum.pdf

Wood, K. L., & Greer, J. L. (2001). Function-based synthesis methods in engineering design. *Formal engineering design synthesis*, 170-227.

Wrisberg, N., Haes, H. A. U. d., Triebswetter, U., & Peter Eder, R. C. (2002). *Analytical Tools for Environmental Design and Management in a Systems Perspective* (Vol. 10). Netherlands: Kluwer Academics Publishers.

Yoon, H.-S., Lee, J.-Y., Kim, H.-S., Kim, M.-S., Kim, E.-S., Shin, Y.-J., . . . Ahn, S.-H. (2014). A comparison of energy consumption in bulk forming, subtractive, and additive processes: Review and case study. *International Journal of Precision Engineering and Manufacturing-Green Technology, 1*(3), 261-279. https://doi.org/10.1007/s40684-014-0033-0

Zimmer, L., & Zablit, P. (2001). " Global Aircraft" pre-design based on constraint propagation and interval analysis. *DGLR BERICHT, 1*(5):77-86.

APPENDIX A DESCRIPTION OF PRODUCT SYSTEMS

Table A.1: Descriptions of product systems used in the LCA (adapted from Dandres (CIRAIG, 2018))

LCA stage	Process	Sub-process	Description
Pre-production	**Commodity production**	**Metal powder/ cylinder**	**Metal powder** is produced through an atomization process in Finland (85% efficiency). The metal powder is packaged in metal cans for their transport. Packaging has been modeled using the weight of an empty can, its volume, and secondary data from the ecoinvent LCI database. The metal powder is transported from Finland to Germany and then to Canada, thus both road and water transports are used. The **metal cylinder** is selected from ecoinvent.
		Metal platform	The **platform** is made in the same metal than the parts (here, Inconel 718) and is produced by APN in Quebec.
		AutoCAD file	The **autoCAD file** is programmed in Quebec.
		Argon	**Argon** is used during the printing is provided by Praxair in Quebec and the quantity is based on the EOSINT M280/290 technical sheets and confirmed with experimental measurements and expert judgement.
Production	**Printing**		The technology used is LPBF-AM, and is modeled using data corresponding to a Renishaw AM2250 SLM **Printer** from the literature (Faludi, Baumers, Maskery, & Hague, 2016). The **electricity** consumed by the LAMSI during the printing of inconel parts has been measured at ETS. This data was used to model the power consumption to produce inconel parts.

Table A.1: Descriptions of product systems used in the LCA (adapted from Dandres (CIRAIG, 2018)) (Continued)

LCA stage	Process	Sub-process	Description
	Filters		**Filters** are needed to operate EOSINT printers. Filters are assumed to be made of polyurethane foam, glass fibre and paper. The rate of replacement for these filters corresponds to the average time of filter replacement at the LAMSI.
	Post treatment	**Stress relief & thermal treatment**	The **stress relief** and **thermal treatment** consist in heating the part (including platform and support if not removed yet) using an industrial electric oven. The electric power of such oven is 1000 W (based on MLF Furnaces, http://www.mlfurnaces.com/bench-top-furnaces/).Corresponding heating up times and electric powers are included.
		Platform and support removals	**Removal** is made with a power saw (sometimes it is made manually in LAMSI but here it has been modeled as always mechanically to better represent the industrial context). It is estimated the saws consumes 500 W during 30 seconds per removal.
		Surface finishing	The **surface finishing** can be made with different tools depending on the part. It is estimated the surface finishing consumes 500 W during 5 minutes.
		Platform flattening	The platform **surface is flattened** with a grinding machine. It is estimated that this operation consumes 1000 W during 30 seconds. Due to lack of data and because it is expected to have a negligible contribution to the part lifecycle, the manufacturing of post-treatment equipment was not included in the method.

Table A.1: Descriptions of product systems used in the LCA (adapted from Dandres (CIRAIG, 2018)) (Continued)

LCA stage	Process	Sub-process	Description
	Maintenance and waste management		A **vacuum cleaner** (made in Germany, transported to Quebec) is used to clean the printer after each printing. This cleaner uses water and a filter to capture the metal powder. It has been modeled as a Ruwac NA35-110 using data from the literature (Faludi et al., 2016). The rate of replacement and duration of cleaning have been determined according to the maintenance rate observed at the LAMSI. The **electric power consumption** of the cleaner is based on the technical sheet of the cleaner. The consumption of water (volume and rate of filling the cleaner) is based on LAMSI cleaning activities. The **mix of water and metal powder** collected by the vacuum cleaner is regularly spilled into a plastic container with addition of **antifoam** and an **anticoagulant**. This container is made of polypropylene and manufactured in Quebec. In the absence of precise information, the antifoam has been modeled as a mix of fatty acid, fatty alcohol and oil, and the anticoagulant as a mix of activated silica, activated bentonite, and metal hydroxides and chlorides. When the plastic container is full, it is handled as a **hazardous waste** and sent with the **used filters** (that are also considered as hazardous wastes due to the presence of metal powder) to a specialized company in Quebec to process it. Because no information was available on the actual hazardous waste treatment, it was modeled with ecoinvent generic processes for hazardous waste.
Use phase			Airplane traveled **distance**: the average airplane speed (829 km/h) is used to compute the traveled distance of airplanes during their **lifetime** (90000 hours). Thus, the airplane traveled distance is 74 610 000 km.

Table A.1: Descriptions of product systems used in the LCA (adapted from Dandres (CIRAIG, 2018)) (Continued and end)

LCA stage	Process	Sub-process	Description
End-of-life	**Types of waste**	**Waste from parts**	At end-of-life, the parts may be **landfilled or recycled**. For both options, it is assumed that the waste management site is located at 50 km from the part user.
		Waste from metal loss	The metal lost during the printing process is considered as **hazardous waste**. The support may be recycled or landfilled. The metal lost during the CM process may be recycled or landfilled.
		Platform	100 times platform reuse. Once it cannot be reused, landfilling or recycling.
		Machines and equipment	The end of life of machines and equipment is not considered since it is expected to have a negligible contribution to part life cycle impacts.
	Waste management options	**Landfilling**	The wastes are sent to a **landfill site** (travelled distance assumed to be 50 km). It is modelled as an inert material (ecoinvent process).
		Recycling	The cut-off approach of ecoinvent has been used. Recyling is excluded. For sensitivity analyses, recycling processes & credits for recycled materials avoiding virgin material production are included. 100% rate applied to the credit for avoiding the production of virgin material (if recycling included).
		Hazardous wastes	Filters, filled with metal powder. Barrel (polypropylene, 100 times reuse) containing water, additives and powder removed with the vaccum cleaner. Barrel capacity is 200 L & additives (antifoam and flocculant) are mixed with the water prior shipping the barrel to the hazardous waste treatment site (travelled distance assumed to be 50 km). Liquid and metal mix considered as a coolant and treated as such. Hazardous wastes stored underground**. Filters contaminated with metal powder a**re assumed to be **deposited undergroun**d and **barrel of waste** are processed as **heat carrier liquid**.

APPENDIX B MANUFACTURING SIMULATIONS

Additive manufacturing

The simulation of the AM process, schematized in Figure C.1, was performed by Victor Urlea (LAMSI).

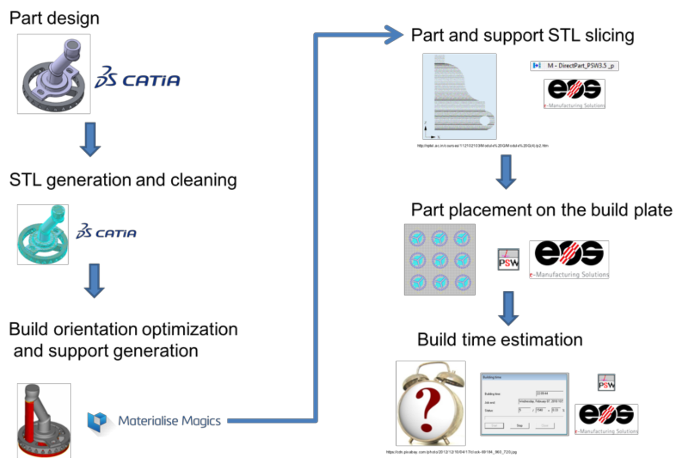


Figure B.1: Build preparation flow chart (source: Victor Urlea, LAMSI)

Machining

The simulation of machining operations, schematized in Figure C.2, was performed by Olivier Boudreau-Rousseau (LAMSI). It was applied to P1(CM reference scenario), but also to P2 and P3 for the post-AM machining operations.

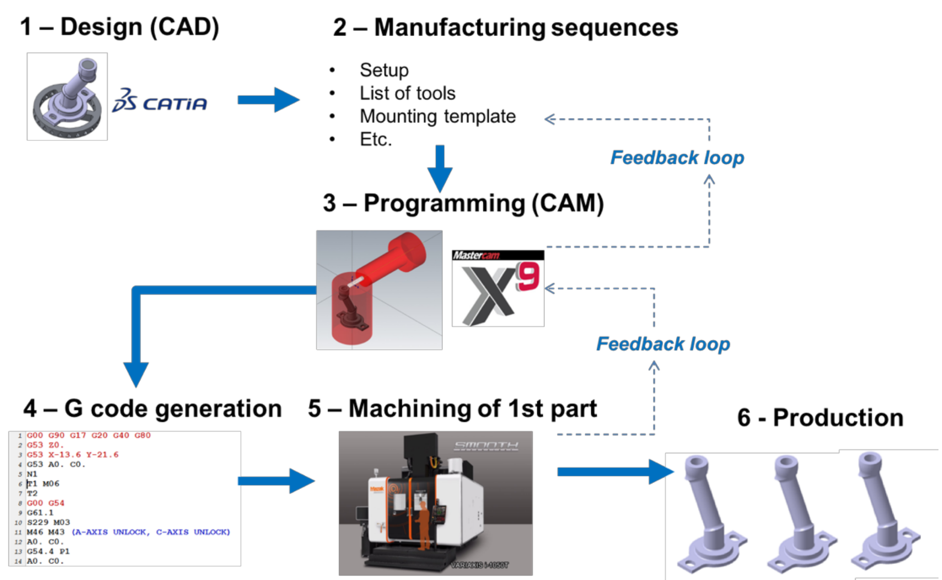


Figure B.2: Machining flow chart (Source: Olivier Boudreau-Rousseau, LAMSI)

Table B.1: Simulations made for a batch of 1

Operation	P3 (AM Optimized)	P2 (AM)	P1 (CM)
AM	One part placed on the build plate		N/A
Machining	Functional surfaces	Functional surfaces	1 cylinder stock

Table B.2: Simulations made for a batch size of 9

Operation	P3 (AM Optimized)	P2 (AM)	P1 (CM)
AM	9 parts placed on the build plate		N/A
Machining	Functional surfaces	Functional surfaces	9 cylinder stocks

Table B.3: Simulations made for a batch size of 90

Operation	P3 (AM Optimized)	P2 (AM)	P1 (CM)
AM	9 parts placed on each of the 10 build plates		N/A
Machining	Functional surfaces	Functional surfaces	90 cylinder stocks

Table B.4: : Build time of the AM parts (P2 and P3) for different batch sizes

Batch size	Part produced	Build time
1	P3	6 h 08 min
	P2	6 h 15 min
9	P3	21h 29 min
	P2	22h 21min
90	P3	214.8 h
	P2	223.5 h

For the **machining simulation**, Olivier Boudreau-Rousseau established a list of the operations needed for each of parts P1, P2 and P3. The Walter's online GPS[14] is used to simulate the tools needed for these operations. Using the tool-related search, the tool category depending on the category of the operation (drilling, milling, etc.) is selected first. The material classification corresponding to the actual case study, Inconel 718, is selected next. Finally, the required machining operations are selected from the list of suggested operations. The specifications included in this section vary with the tool category and operation selected. For example:

i. Operation type: pre machining, finishing, or pre machining and finishing
ii. Workpiece surface condition: pre-machined, light skin or heavy skin
iii. System stability: excellent, good or high stability
iv. Operation parameters: depth, width, length, interruption ratio
v. Tool parameters: cutting edge diameter, minimum and maximum cutting edge diameter

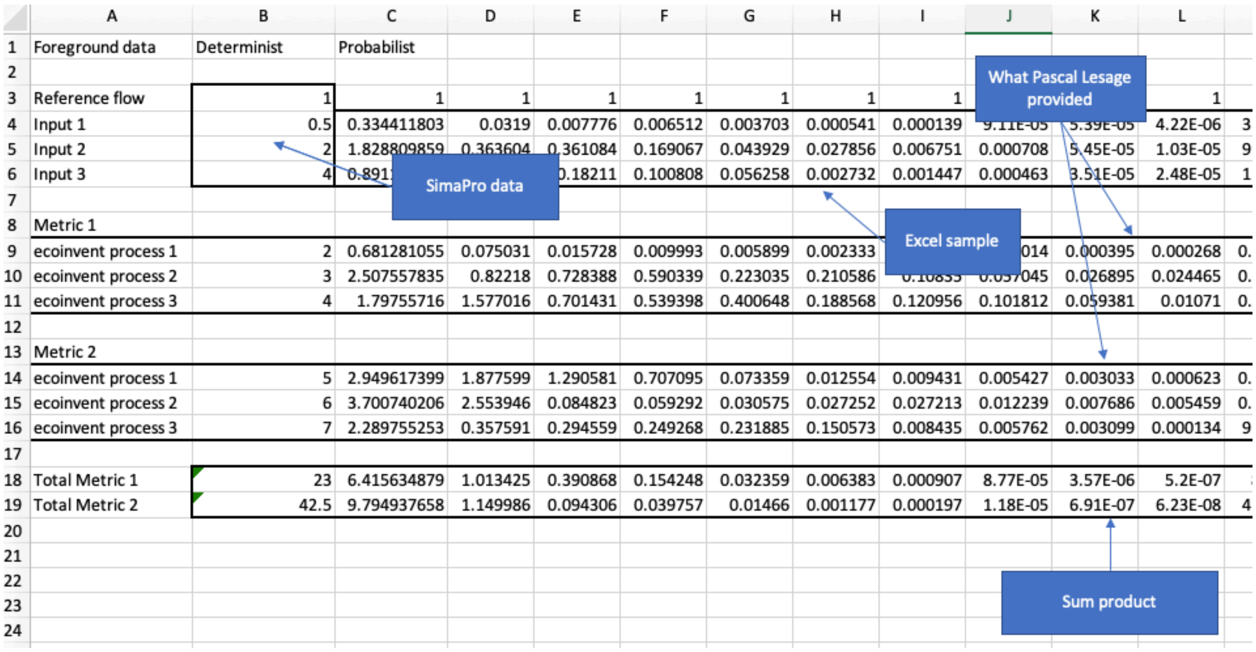
[14] Walter GPS 4.2.1 (www.gps.walter-tools.com)

The GPS is then able to suggest a list of tools from Walter's inventory which are able to conduct the machining operation. It also suggests the cost per task accomplished (Table C.5). The exchange rate used is 1.59 Canadian dollar for 1 euro.

Table B.5: Machining operations estimated with Walter's tools

	P3 (AM Optimized)	**P2 (AM)**	**P1 (CM)**
Operations	7	7	22
Cutting tools	4	4	8
Mounting template	1 or more	1 or more	1 or more
Machining time	16 min 15 sec	16 min 15 sec	47 min 22 sec
Cost per task (euro)	14.04 €	14.04 €	65.99 €
Cost per task (CAD)	22.32 $	22.32 $	65.99 $

APPENDIX C PRESAMPLED AGGREGATED DATASETS (LCA)



	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Foreground data	Determinist	Probabilist										
2													
3	Reference flow	1	1	1	1	1	1	1	1	[illegible]	[illegible]	1	
4	Input 1	0.5	0.334411803	0.0319	0.007776	0.006512	0.003703	0.000541	0.000139	9.11E-05	5.39E-05	4.22E-06	3
5	Input 2	2	1.828809859	0.363604	0.361084	0.169067	0.043929	0.027856	0.006751	0.000708	5.45E-05	1.03E-05	9
6	Input 3	4	0.891[illegible]	[illegible]	0.18211	0.100808	0.056258	0.002732	0.001447	0.000463	3.51E-05	2.48E-05	1
7													
8	Metric 1												
9	ecoinvent process 1	2	0.681281055	0.075031	0.015728	0.009993	0.005899	0.002333	[illegible]	[illegible]014	0.000395	0.000268	0.
10	ecoinvent process 2	3	2.507557835	0.82218	0.728388	0.590339	0.223035	0.210586	[illegible]	[illegible]	0.026895	0.024465	0.
11	ecoinvent process 3	4	1.79755716	1.577016	0.701431	0.539398	0.400648	0.188568	0.120956	0.101812	0.059381	0.01071	0.
12													
13	Metric 2												
14	ecoinvent process 1	5	2.949617399	1.877599	1.290581	0.707095	0.073359	0.012554	0.009431	0.005427	0.003033	0.000623	0.
15	ecoinvent process 2	6	3.700740206	2.553946	0.084823	0.059292	0.030575	0.027252	0.027213	0.012239	0.007686	0.005459	0.
16	ecoinvent process 3	7	2.289755253	0.357591	0.294559	0.249268	0.231885	0.150573	0.008435	0.005762	0.003099	0.000134	9
17													
18	Total Metric 1	23	6.415634879	1.013425	0.390868	0.154248	0.032359	0.006383	0.000907	8.77E-05	3.57E-06	5.2E-07	[illegible]
19	Total Metric 2	42.5	9.794937658	1.149986	0.094306	0.039757	0.01466	0.001177	0.000197	1.18E-05	6.91E-07	6.23E-08	4
20													
21													
22													
23													
24													

Figure C.1: Procedure to collect presamples and compute the uncertainty analysis

APPENDIX D STOCHASTIC RESULTS

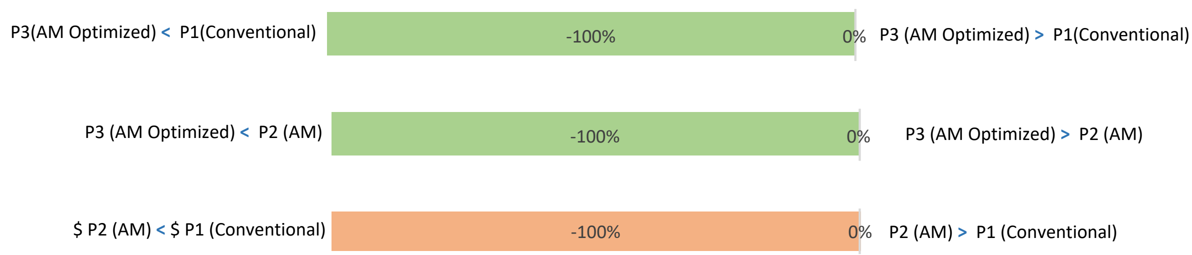


Figure D.1: Probability of a scenario being better than another between P1 (CM), P2 (AM) and P3 (AM Optimized) in terms of NOx emissions

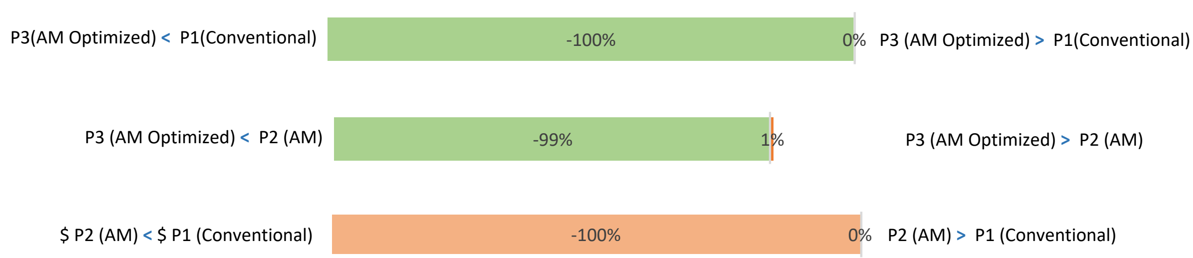


Figure D.2: Probability of a scenario being better than another between P1 (CM), P2 (AM) and P3 (AM Optimized) in terms of PM emissions

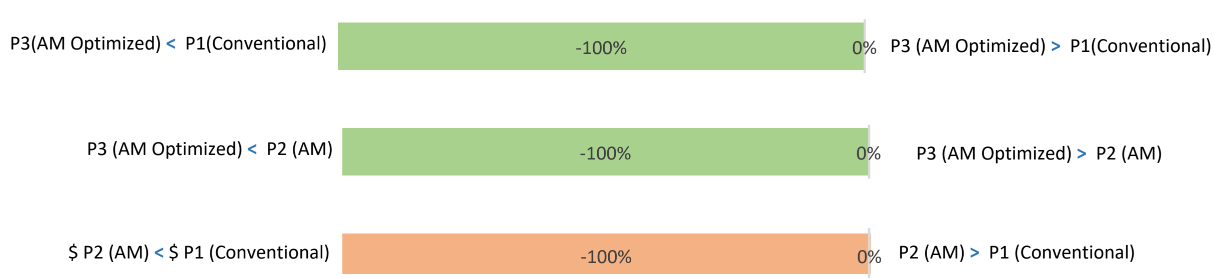


Figure D.3: Probability of a scenario being better than another between P1 (CM), P2 (AM) and P3 (AM Optimized) in terms of impacts on resources

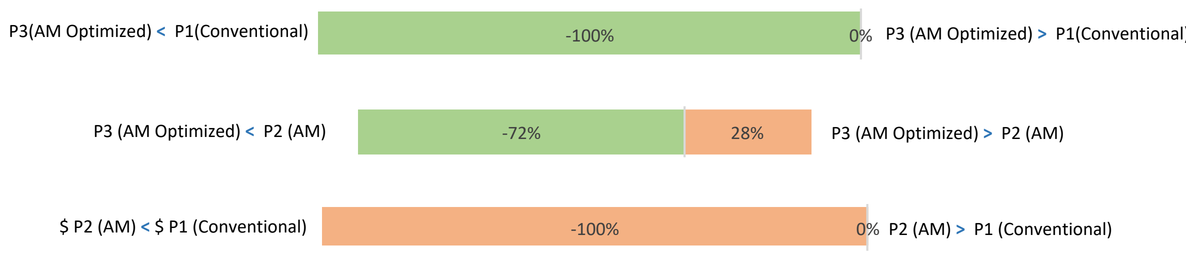


Figure D.4: Probability of a scenario being better than another between P1 (CM), P2 (AM) and P3 (AM Optimized) in terms of impacts on human health

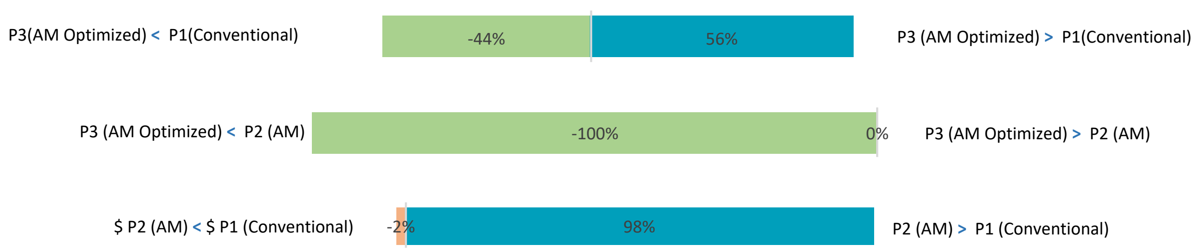


Figure D.5: Probability of a scenario being better than another between P1 (CM), P2 (AM) and P3 (AM Optimized) in terms of impacts on ecosystems quality

APPENDIX E SENSITIVITY ANALYSES

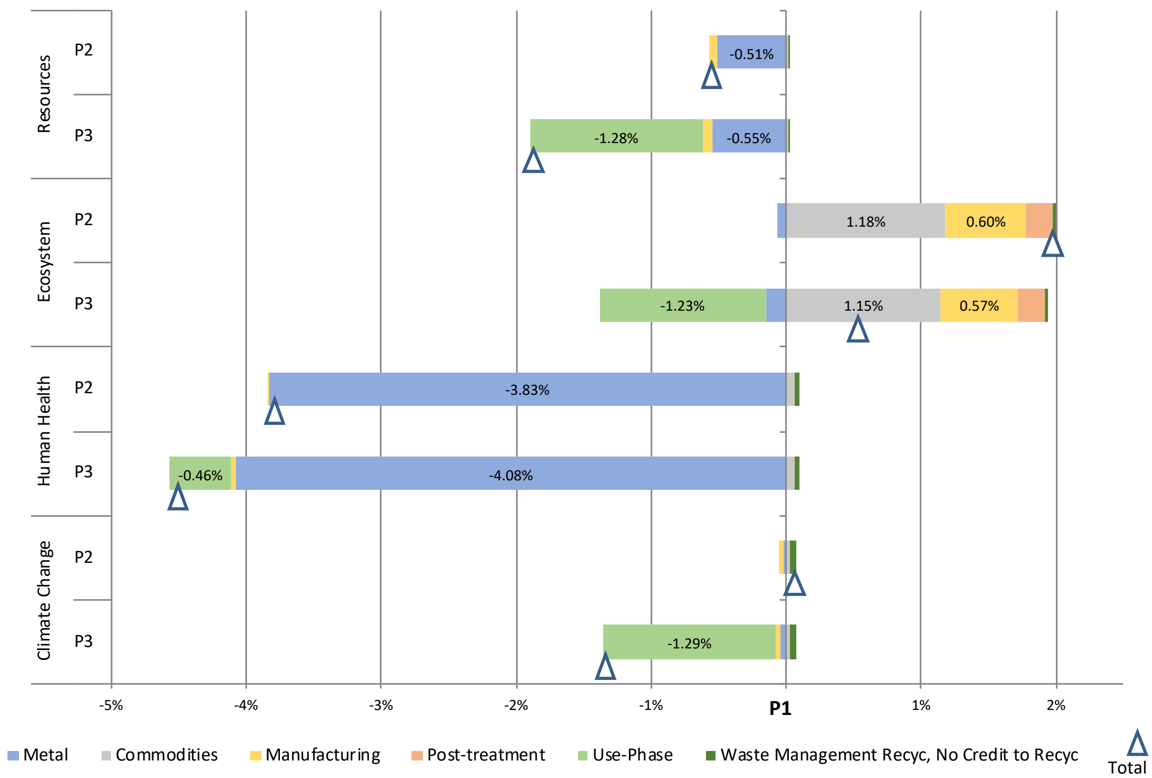


Figure E.1: Sensitivity analysis of life-cycle impacts to recycling

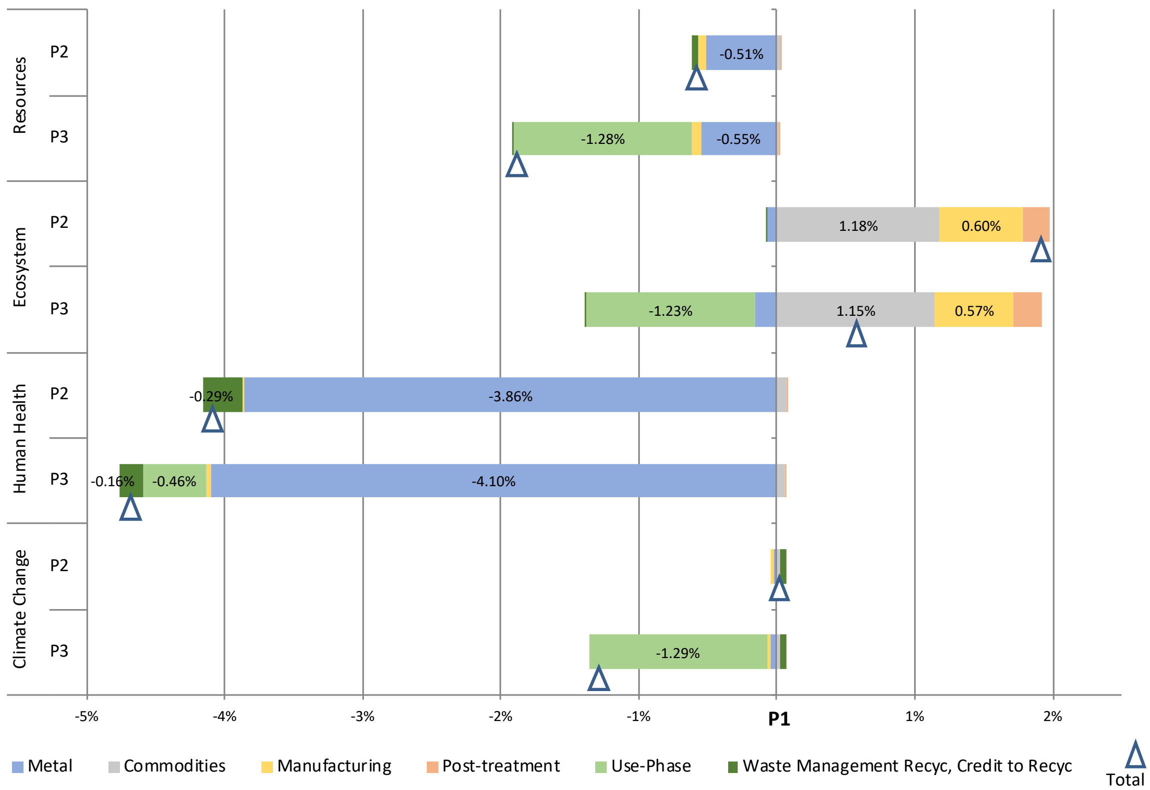


Figure E.2: Sensitivity analysis of life-cycle impacts to recycling with credit to recycling

The cost of landfilling and recycling is assumed to be the same. Therefore only the credit given to recycling contributes to lowering the life-cycle cost.

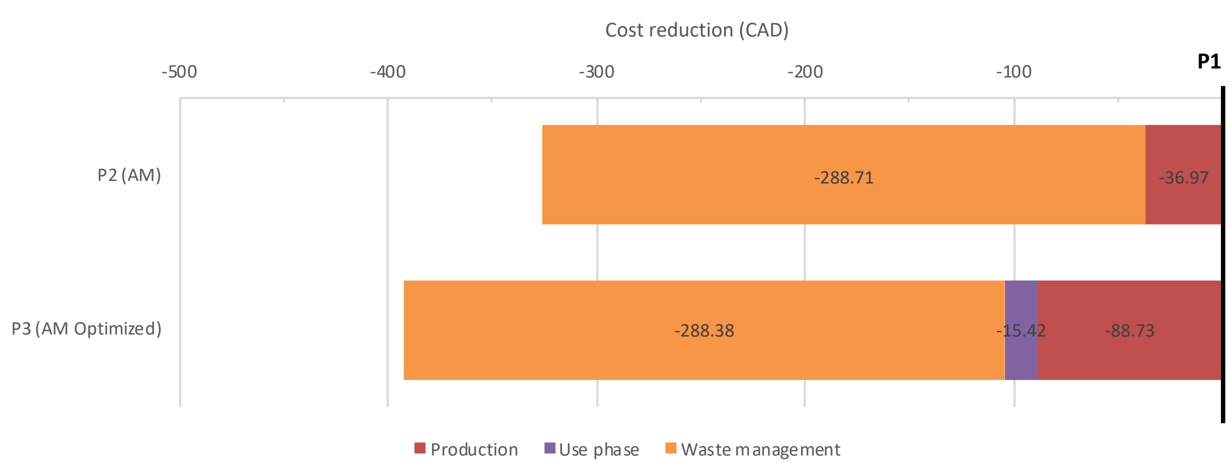


Figure E.3: Sensitivity analysis of life-cycle cost to credit given to recycling. The cost of P2 (AM) and P3 (AM Optimized) are plotted relatively to P1 (CM)

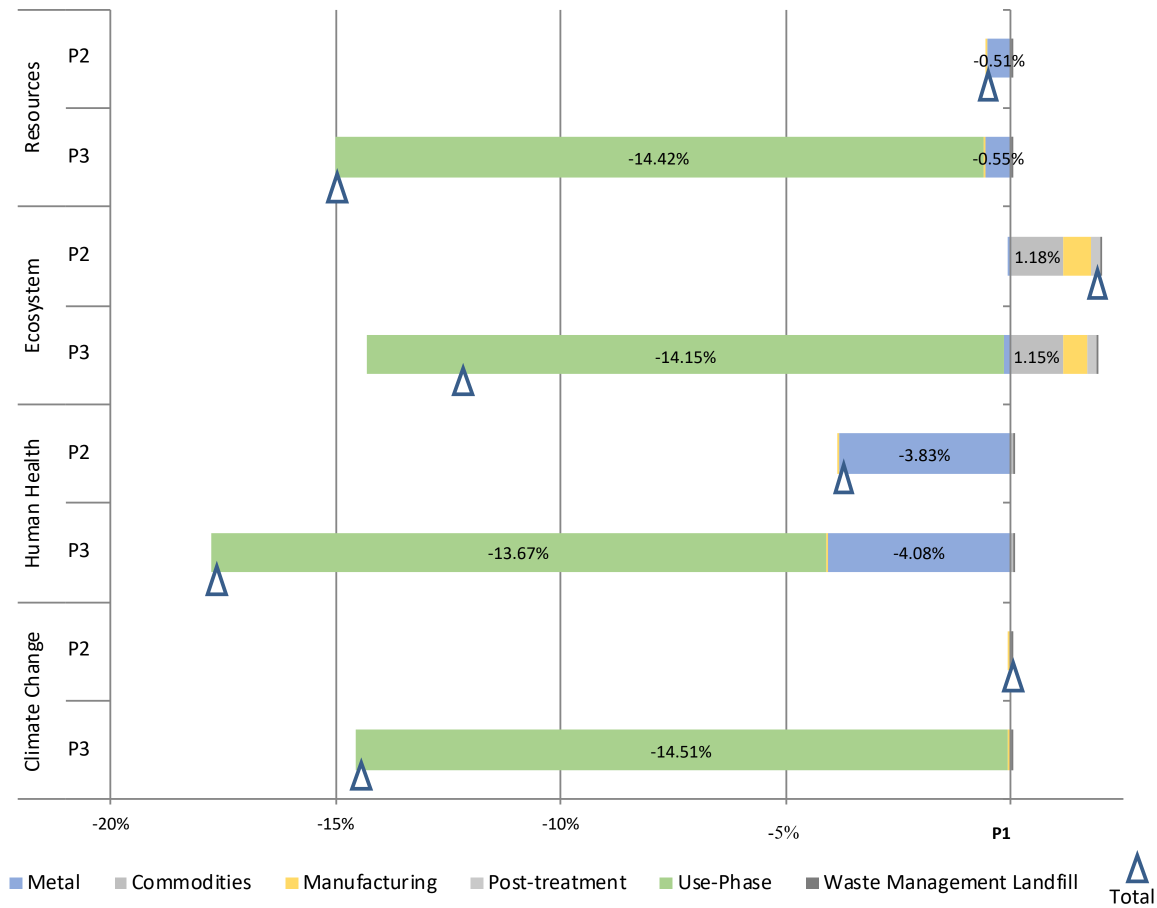


Figure E.4: Sensitivity of life-cycle impacts to the fuel consumption modelling (considered proportional to the mass transported)

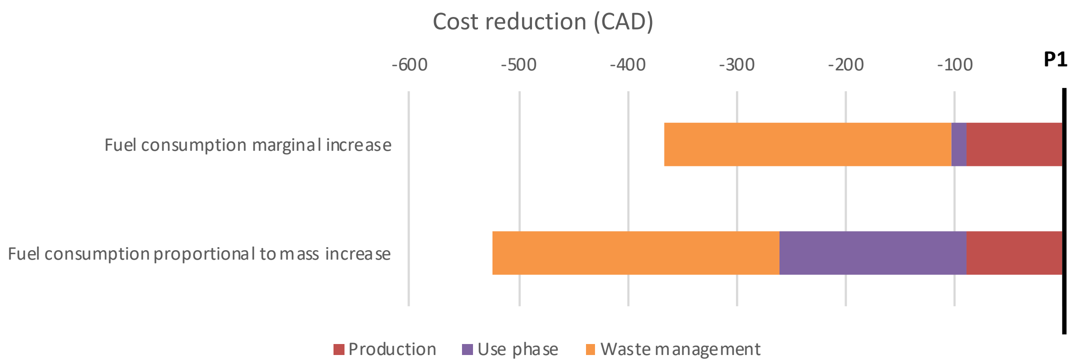


Figure E.5: Sensitivity of life-cycle cost to the fuel consumption modelling. P3 (AM Optimized) is plotted relatively to P1 (CM)

APPENDIX F MIDPOINTS CONTRIBUTION TO ENDPOINTS

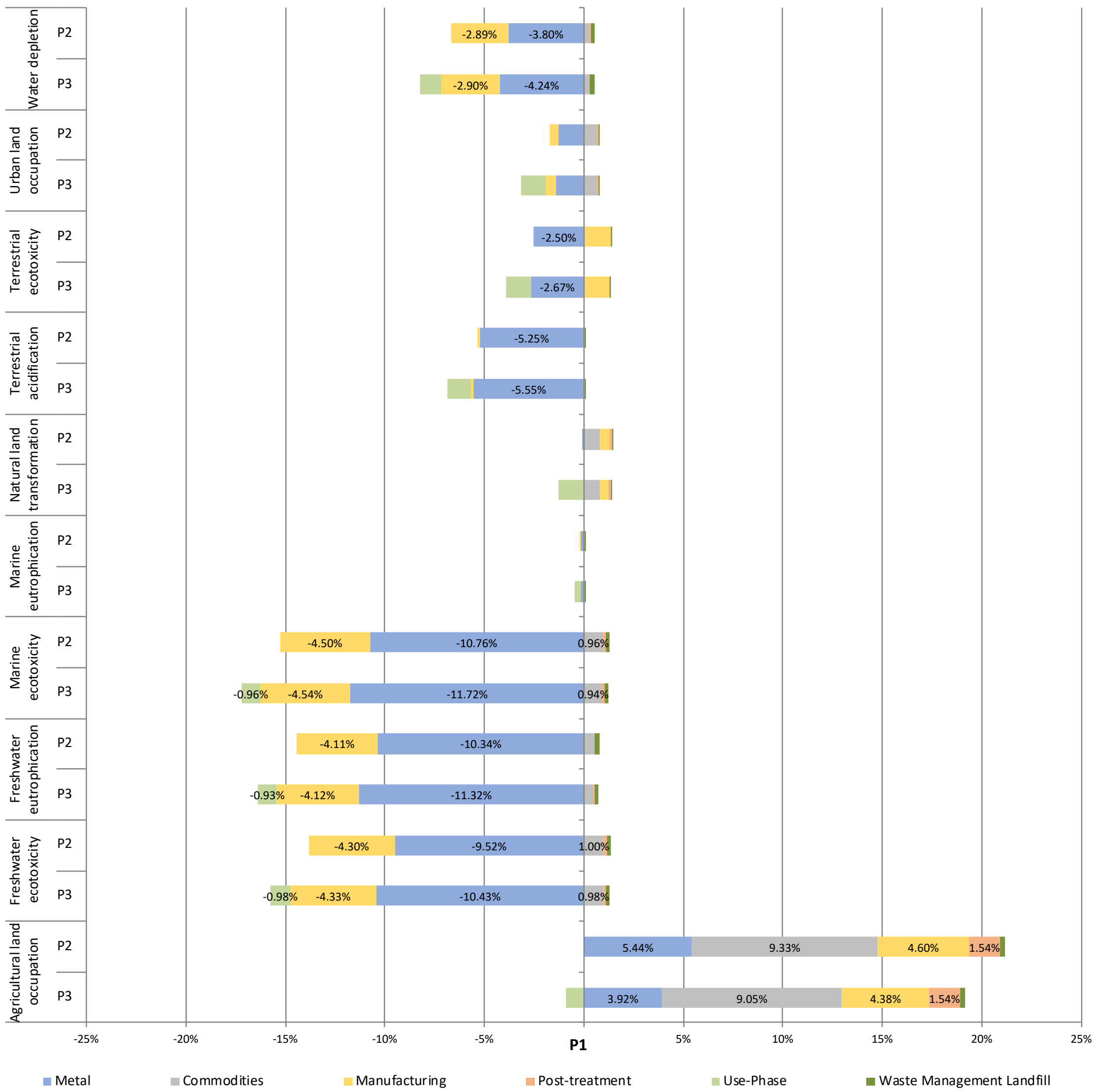


Figure F.1: Midpoints categories for P2 (AM) and P3 (AM Optimized) relatively to P1 (CM). The midpoints scores are expressed as their contribution to ecosystems quality

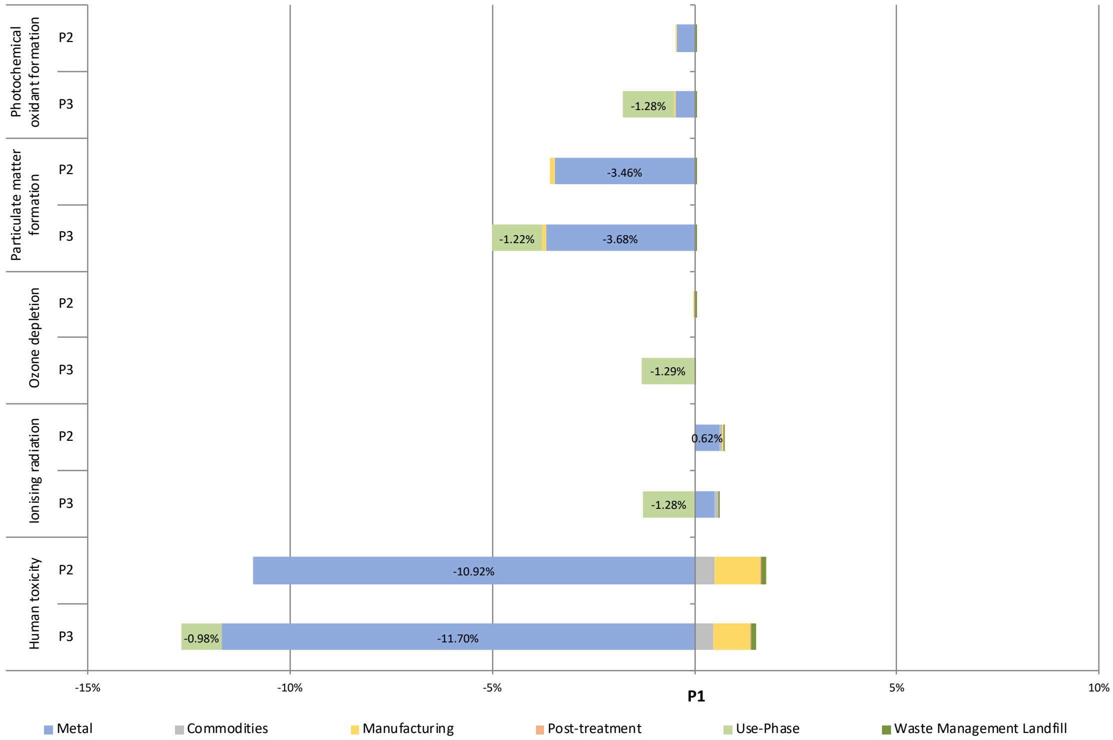


Figure F.2: Midpoints categories for P2 (AM) and P3 (AM Optimized) relatively to P1 (CM). The midpoints scores are expressed as their contribution to human health

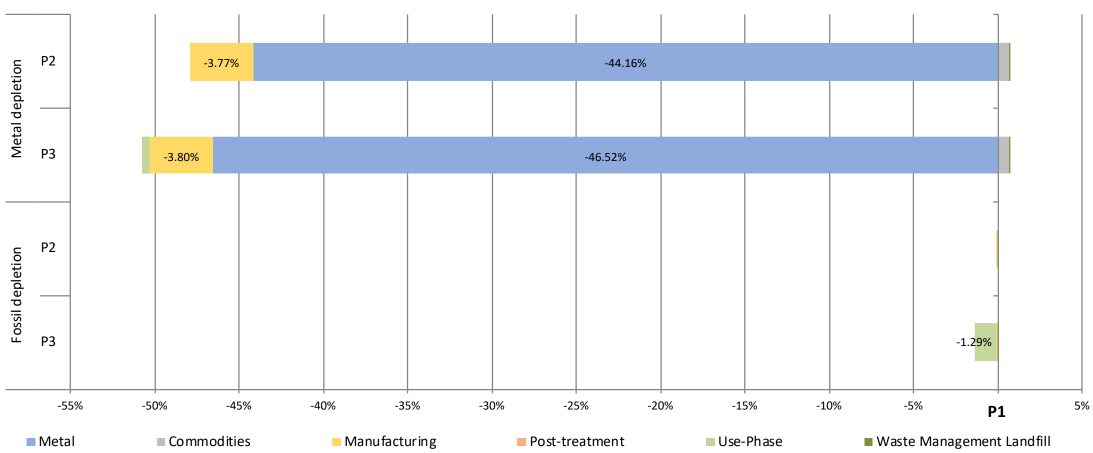


Figure F.3: Midpoints categories for P2 (AM) and P3 (AM Optimized) relatively to P1 (CM). The midpoints scores are expressed as their contribution to resources

The results show that there is a shift in the total impacts of P1, P2 and P3 for the midpoint "agricultural land occupation" (P2 and P3 have greater impacts for this midpoint category than P1).

The impacts are mainly due to intensive forest occupation (for example, because of Inconel metal powder which is produced in Finland using electricity low voltage).