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Decision Support System for Sustainable Production of Spare Parts with Additive Manufacturing

Master's thesis in Mechanical Engineering
Supervisor: Mirco Peron
January 2023

Master's thesis

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Abstract

Additive manufacturing (AM) has opened new possibilities in the spare part sector, where conventional manufacturing (CM) has limitations. With on-demand abilities, toolless production and design freedom, AM has improved the supply chain (SC) to a more flexible and efficient form. Physical spare parts are transformed into digital 3D files, changing large warehouses into digital databases. This significantly impacts sustainability, especially the environmental impact per produced spare part, which is a high priority due to the well-known challenges created by climate change. The literature offers a wide selection of studies on the different impacts of a change from CM to AM or comparing both based on the environmental impacts. Several of these studies suggest that AM is a viable choice to replace CM due to reduced environmental impact and economic benefits. The literature also provides several papers comparing different AM methods, but in an SC design comparison of central and decentral production, also called on-site and off-site, is limited. No studies offer decision support to managers or practitioners when choosing the optimal SC design for sustainable AM of spare parts. When looking at sustainable SC design options for spare parts, several papers have investigated this with varying results. Similarities in the parameters used are production and transportation. The energy mix is mentioned several times as a parameter with a significant impact but is rarely included in calculations and comparisons. During this thesis, a mathematical model is developed to calculate on-site and off-site total carbon emissions and compare these. Then a parametric analysis will be performed where the result is fed into a decision tree algorithm to produce a decision support system (DSS) to assist managers and practitioners when choosing SC design. The results show that energy mix is the main parameter to impact the SC design choice.

Sammendrag

Additiv produksjon (AM) har åpnet for nye muligheter i reservedelssektoren, hvor konvensjonell produksjon (CM) har begrensninger. Med evner til å produsere ved etterspørsel, verktøy løs produksjon og designfrihet, har AM forbedret forsyningskjeden (SC) til en mer fleksibel og effektiv form. Fysiske reservedeler omdannes til digitale 3D-filer, og endrer store varehus til digitale databaser. Dette påvirker bærekraften betydelig, spesielt miljøbelastningen per produsert reservedel, som er høyt prioritert på grunn av de velkjente utfordringene klimaendringene har skapt. Litteraturen tilbyr et bredt utvalg av studier som ser på de ulike konsekvensene en endring fra CM til AM har, eller sammenligner begge basert på miljøpåvirkningene. Flere av disse studiene tyder på at AM er et fullverdig valg for å erstatte CM på grunn av redusert miljøpåvirkning og økonomiske fordeler. Litteraturen inneholder også flere artikler som sammenligner ulike AM-metoder, men ved en SC-designsammenligning av sentral og desentralisert produksjon, også kalt «på området» (on-site) og «utenfor området» (off-site), er veldig begrenset. Ingen studier tilbyr beslutningsstøtte til ledere eller utøvere når de skal velge det optimale SC-designet for bærekraftig AM av reservedeler. Når man ser på bærekraftige SC-designalternativer for reservedel produksjon, har flere artikler undersøkt dette med varierende resultater. Ved analysene av SC-designalternativene finnes det likheter i parameterne som er inkludert. Produksjon og transport er ofte brukt i slike analyser. Energimiksen nevnes flere ganger som en parameter med en betydelig innvirkning i slike analyser, men tas sjelden med i beregninger og sammenligninger. I løpet av denne avhandlingen er det utviklet en matematisk modell for å beregne totale karbonutslipp on-site og off-site, deretter blir de sammenlignet. Deretter vil det bli utført en parametrisk analyse hvor resultatet mates inn i en beslutnings tre algoritme for å produsere et beslutningsstøttesystem (DSS) for å hjelpe ledere og brukere ved valg av SC-design. Resultatene viser at energimiks er hovedparameteren for å påvirke et SC-designvalg.

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1 Introduction

Additive Manufacturing (AM) is not a new technology, but the development of AM technology has opened new areas where AM can be beneficial to implement. AM is increasingly important in spare parts productions because it allows toolless manufacturing and ample design freedom. This eliminates lead time in tool change and assembly time by merging several components into one part (Holmström et al., 2010). One of the essential benefits of AM is the opportunity to produce spare parts when needed, "on-demand", thus reducing or even eliminating large inventory levels that are costly and unnecessary. This opens the possibility of having a digital inventory of 3D files instead of physical spare parts, often referred to as a "digital warehouse" in the literature (Cardeal et al., 2022; Chekurov et al., 2018). The availability is crucial for producers to reduce the risk of high costs due to downtime, making spare part management a central part of preventing such expenses. Spare parts are usually characterized by shifting demand, making it hard to predict the demand. With conventional manufacturing (CM), the general solution to this difficulty is large warehouses with various spare parts. This leads to an expensive supply chain (SC) with low flexibility due to the cost-intensive storage facilities and tied-up capital in the spare parts stored. AM characteristics can provide an alternative SC where the mentioned digital warehouse is implemented. The on-demand capabilities drastically reduce the need for high inventory levels, leading to a more cost-efficient and flexible spare part production. There are many options for inventory management (IM), but most companies have some inventory at their production facility (on-site), even though a central warehouse is the primary IM solution. These on-site inventories can then be transformed into on-site production facilities for spare parts using AM. The transportation cost of bringing the spare part to the production facility is eliminated, reducing cost and CO_2 emission from the transportation (Sasson & Johnson, 2016). It is undeniable that AM production of spare parts in small volumes is more efficient than CM, with a reduction of inventory levels, on-demand, and reduced complexity in supply chains, to mention a few benefits. When adding the on-site production factor and eliminating the transportation, the location of spare part production seems unambiguous with the environment in mind. However, some countries produce high CO_2 emissions due to fossil-based energy production. This challenges on-site production due to the large variation in the energy mix for different countries. The importance of the energy mix is due to the high energy consumption when using AM technology, making the energy mix a vital parameter when looking at the environmental footprint of produced spare parts. This insight may suggest that on-site might not always be the best option from an environmental point of view and opens the possibility that off-site production can have a lower environmental footprint due to the differences in energy mixes for different countries. Even with the transportation added to the off-site production, this has potentially a lower environmental footprint than producing it on-site. When calculating the environmental footprint of spare parts, life cycle phases relevant to a given SC and production method must be evaluated, which is done in this thesis. This thesis aims to find out when it is environmentally convenient to produce on-site, and whether it is always suitable to produce on-site or if there are situations where off-site is more environmentally friendly, meaning less CO_2 is produced based on a control volume consisting of relevant life cycle phases. The thesis will also try to answer which parameters are important to emphasize when choosing between on-site and off-site, also called the SC design. This results in a decision support system (DSS) presented as a decision tree to help managers and practitioners choose the most sustainable SC design based on their situation.

This is the first work where something like this is done. In the literature, nothing similar can be found, only papers with partial similarities. One of these is the work done by Rupp et al. (2022), where they aim to compare the subtractive and additive production of metal parts by calculating the carbon emissions produced during production and transportation. The comparison of subtractive production is irrelevant, but the life cycle phases and parameters used to calculate the emissions are mostly similar. Production and transport (two similar phases used), using the same transport modes (ship, train, truck and planes) and energy mix as a parameter in the carbon emissions calculations. Another similar work was done by Cantini et al. (2022), where methods like a mathematical model and decision tree were made to find the most optimal SC design to minimize costs instead of carbon emissions. Moreover, a DSS is created to guide managers and practitioners in choosing SC designs, which compare AM against CM and centralized- against decentralized production. The automotive industry is one sector where spare parts are a huge part of the business after-sales, where the balance between inventory cost and service level is critical, as well as the risk of obsolete spare parts. Isasi-Sanchez et al. (2020) investigate these problems with AM as a solution from a sustainability point of view using quantitative analysis. The results indicate that the location of production is an essential environmental aspect due to the reduction in transportation and inventories. This is consistent with the on-site argumentation from earlier but also limited to this for this paper, leaving out the energy mix related to the location. The energy mix is discussed in several papers. Still, it is not set in the context of comparing different energy mixes in other situations in an on-site/off-site scenario (Cerdas et al., 2017; Rupp et al., 2022; Walachowicz et al., 2017a). The general approach is to compare the AM with CM, where AM often are placed on-site to eliminate unnecessary transport. Cerdas et al. (2017) point out that the regional electricity mix (energy mix) can significantly influence the emission for production using AM. However, the energy mix is not included in the environmental analysis. Also, the production location is decided to be on-site regardless of the energy mix, and the economic side of cheap electricity is prioritized over the environmental aspect. As mentioned, the literature has some similarities to what this thesis aims to provide. However, with the introduction of DSS for managers and practitioners for choosing optimal SC design based on environmental impact, this thesis will provide new insight into the literature.

This thesis is divided into five sections: Introduction, Theoretical background, Methodology, Result and discussion, and Conclusion. The Theoretical background section will give the theoretical insight needed to understand the different aspects implemented in the thesis. It will also explain the control volume used in this research. In the Methodology section, the working process for the results is given, and which tools have been used throughout this process. The results from the research will be presented and discussed in the Result and discussion section. The last section will be a conclusion, where the main features from the result section are presented. Moreover, the limitations of this thesis and future research are also included in the last section.

2 Theoretical background

The theoretical background starts with a brief introduction to Additive Manufacturing (AM), with a more thorough explanation of the selective laser melting production method used in this thesis (Subsection 2.1). With the AM in mind, the life cycle for spare parts is presented by dividing it into phases (Subsection 2.2). These phases are assessed to find which phases are relevant to include in the parametric analysis, and these phases are defined as the control volume (Subsection 2.3). Lastly, we review the literature pertinent to this thesis (Subsection 2.4).

2.1 Additive Manufacturing

Additive Manufacturing is now a well-known technology and well-documented in the literature. Several different technologies are collected under the term AM, but the core principle is the layer-by-layer method, where you build from the ground up. The most common technology used for metal material is Powder Bed Fusion (PBF), where the metal powder is applied to the building platform with a layer height of 30–50 μm (Rupp et al., 2022). The building platform is placed inside a chamber with an inert gas atmosphere in some cases and a vacuum in others. Then the layered material is sintered or melted using a laser, electron beam, or a fusing agent. After the first layer, the building plate is lowered, and the process starts over again and is repeated until the part is complete. The building plate is heated to make the merging between the layers as rigid as possible. There are five methods used in PBF: Selective Laser Sintering (SLS), Selective Laser Melting (SLM), Direct Metal Laser Sintering (DMLS), Electron Beam Melting (EBM), and Multi Jet Fusion (MJF). Technology advances are continuous, and new methods and technology are regularly presented to the market. It must be noted that there may be other methods on the market that are not included here.

In this thesis, the values used in the parametric analysis are based on the SLM method. SLM and DMLS use a laser for fusing the material, where the only difference is the temperature created by the laser. Metal powder is evenly distributed on the building plate using a feeding system and a re-coater blade that drags powder across the building surface (Sames et al., 2016). The SLM process is illustrated in Figure 1. SLM operates at a higher temperature than DMLS. The metal powder is fully melted by the laser, making the metal particles fused and creating the possibility of strong spare parts or prototypes. In the DMLS process, the lower temperature connects the metal particles through sintering. This limits material options to alloys and the produced parts' toughness. The layering process leads to challenges in the mechanical properties due to the residual stress that builds up inside the printed part, possibly exposing the part to distortion. Some post-production processes can be used to reduce these weaknesses, like heating- and pressure treatment. Also, the surface of the produced component may need some post-production processes to meet requirements set by the end-user or customer, like milling and polishing.

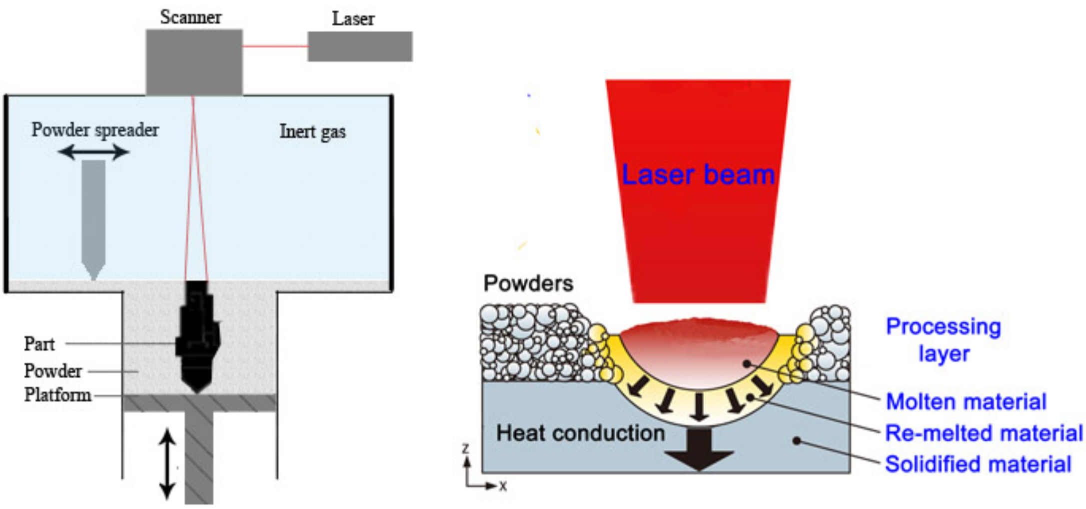

Figure 1: An illustration of the SLM process

Of all the PBF technologies, SLM is one of the most mentioned methods in the literature and was used and studied in a preliminary literature study to this thesis. The preliminary study was the specialization project for the author and had two objectives, the first was to find which life cycle phases were used in the literature when using AM, and the second was to find values for phases defined by a control volume based on what was needed for this study. The result of these objectives is used and partly presented in Sections 2.2 and 2.3.

2.2 The life cycle for spare parts

In this section, defining the phases that contribute to the environmental footprint in the life cycle for the spare parts is done. The life cycle presented here is based on the result found in the specialization project. As shortly described, the first target was to present a consensus for the different life cycle phases found through a selective literature review (SLR). After the consensus, a control volume is established based on the most critical phases for assessing the environmental impact when locating a production for AM-produced metal spare parts. Further, each phase in the control volume is described in detail for the second target, and the values for the control volume are also found through the SLR. These values are also the foundation for the parameters used in this thesis, and the result of this is partly replicated in Table 1 and Table 2. Figure 2 illustrates the phases found and considered during the SLR of the specialization project (the result of the SLR is displayed in Appendix A - SLR result). Each phase will now be explained from the starting point (Raw material extraction) and continue in a clockwise manner using Figure 2 as a guide. When referring to "the literature review", it is the SLR performed in the specialization project it refers to.

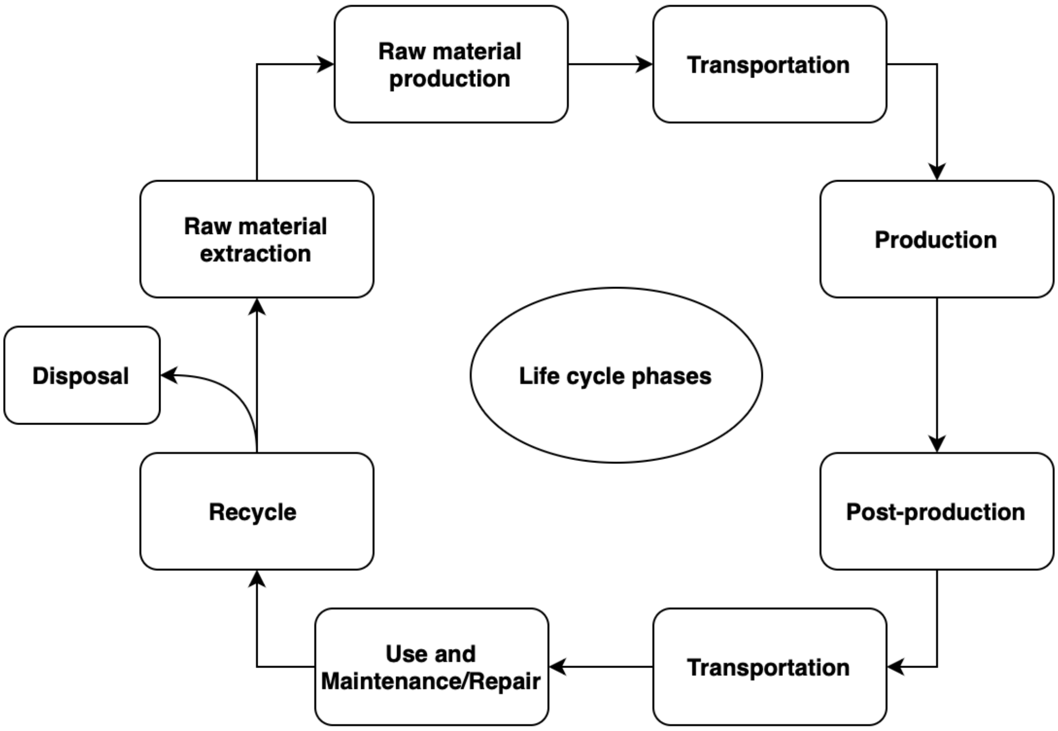

Figure 2: An illustration of the life cycle phases

The start of the life cycle for a spare part is the extraction of the raw material used in the production. This phase includes mining and refining before it is shipped to the raw material production used directly in the AM production. This is an energy- and emission-intensive phase due to the heavy machinery needed to extract the material from the hard rocks. The literature review revealed that this is often a mentioned phase and is considered in the analyses. Still, in-depth explanations of the processes used to produce the numbers presented are rarely written. The keywords used in the literature review were aimed at papers with more general life cycle analyses, like the well-known Life Cycle Analysis (LCA). This general approach can partly explain why several papers are brief and not detailed in describing the phases used. Still, there were other phases with much more detailed descriptions than the raw material extraction phase.

As mentioned earlier, this thesis uses SLM values and will use the SLM method as a base when evaluating the different phases. The raw material used in the production of SLM parts is powder, and specifically for this case, is stainless steel powder. There are several methods to produce this powder by handling the rough material from the extraction to produce a fine powder. The literature review revealed that one method is more used than another, the atomization process. The atomization process starts by melting the metal in a furnace, followed by transferring the molten metal to a spray chamber where it is atomized by sprayed out the melt simultaneously as compressed air, inert gas, or water jet at high-pressure (Nagarajan & Haapala, 2017) sprayed at the melt, as Figure 3 shows. This leaves the finished powder that is used in the production phase. There are several methods to perform the atomization process, Figure 3 present four examples leading to the same result. The literature is not precise in what method is used when describing the raw material production phase, generally just saying the atomization process is used without further explanation.

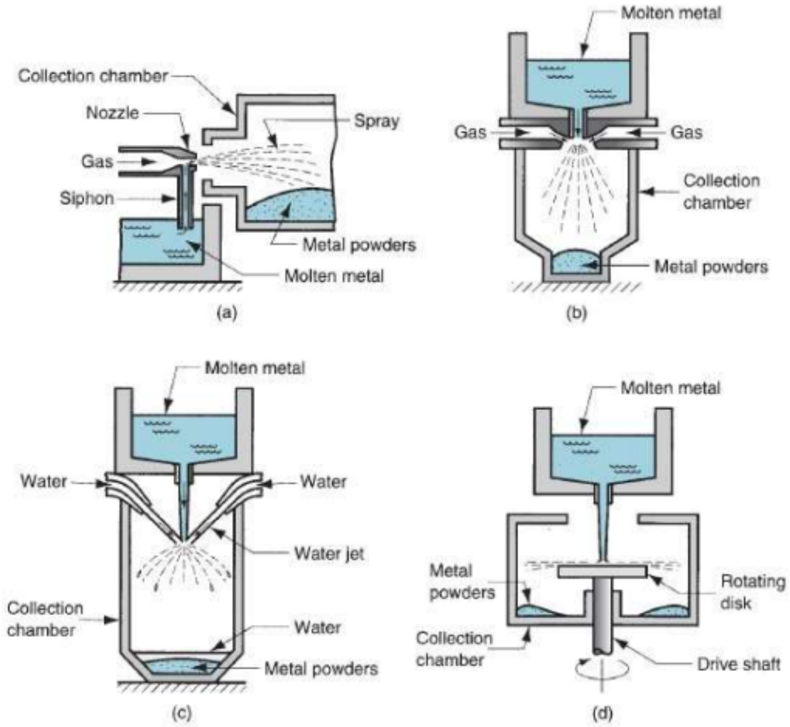

Figure 3: Illustration of different atomization processes (Kale, 2020)

For the transportation phase, there are several possibilities on how to define this phase and what to include. Theoretically, you can include every material- and product handling from the raw material extraction to the disposal/recycling phases and between the phases. If the analysis aims to see the more prominent lines, the small handling operations have a marginal influence on the total transport contribution to the environmental footprint. The most common transport modes stated in the literature review were plane, ship, train, and truck, and the main shipping of the part is most commonly defined as the transportation phase.

Since this thesis has a sustainable focus on the environmental effects, the production phase contribution to the analysis is energy consumption, which is converted to carbon emission. Other minor operations and processes that could be included in this phase are neglected. As mentioned several times in the literature and earlier in this thesis, one of the main drawbacks of AM is the energy-intensive production process. From heating the building plate, the powder distribution system, and the laser as the primary energy user. The finished part often needs some post-production treatment depending on the requirements set by regulations or end-user. With different requirements and materials used in the printing process, many possible processes are caught under the post-production phase. As the literature review revealed, the post-production phase and the environmental assessment of this phase are minimal (Liao & Cooper, 2020). The SLM printing process often needs post-production processes, which are already mentioned, but in short, milling- and polishing processes for surface and heat and pressure treatment for the material properties.

In the literature, the use- and maintenance/repair phase is often entangled, meaning that a phase can be called the "use phase" but also includes maintenance and repair.

Often this phase is neglected with the arguments that there is no significant associated energy consumption to this (Lyons et al., 2021b). Other papers look at the effects that the AM can provide regarding the use phase and compare the effects with other manufacturing processes. Liao and Cooper (2020) use life cycle phases to cover different aspects of the environmental impact of AM. In the use phase, they emphasize the positive effect of a lightweight AM-produced part on the fuel economy, leading to reduced greenhouse gas emissions (Liao & Cooper, 2020). If the perspective is a whole lifetime for a spare part, this phase would have significantly influenced the environmental footprint.

The recycling and disposal phases are defined differently in the literature, and in several cases, they are combined into a phase called "end of life". In papers where a comparative analysis of AM and CM is done, the recycle can be an important factor due to the reuse through recycling. When materials can be reused with recycling instead of disposal, it reduces the need for raw material extraction and affects the environmental footprint.

2.3 Control volume

With the life cycle phases defined in the previous section, a control volume can now be established for the relevant phases of this thesis. Due to the intentions of this study, only some of the phases are relevant to include in the parametric analysis. Since we are comparing AM with AM, the parameters that change between scenarios are the location and transportation. The raw material extraction, raw material production, use and maintenance, and at last, the recycling/disposal will all be identical when comparing the same production method (AM) and will therefore cancel each other out. This means that six of the nine phases are not relevant for the analysis, and we can therefore establish a control volume based on the defined life cycle.

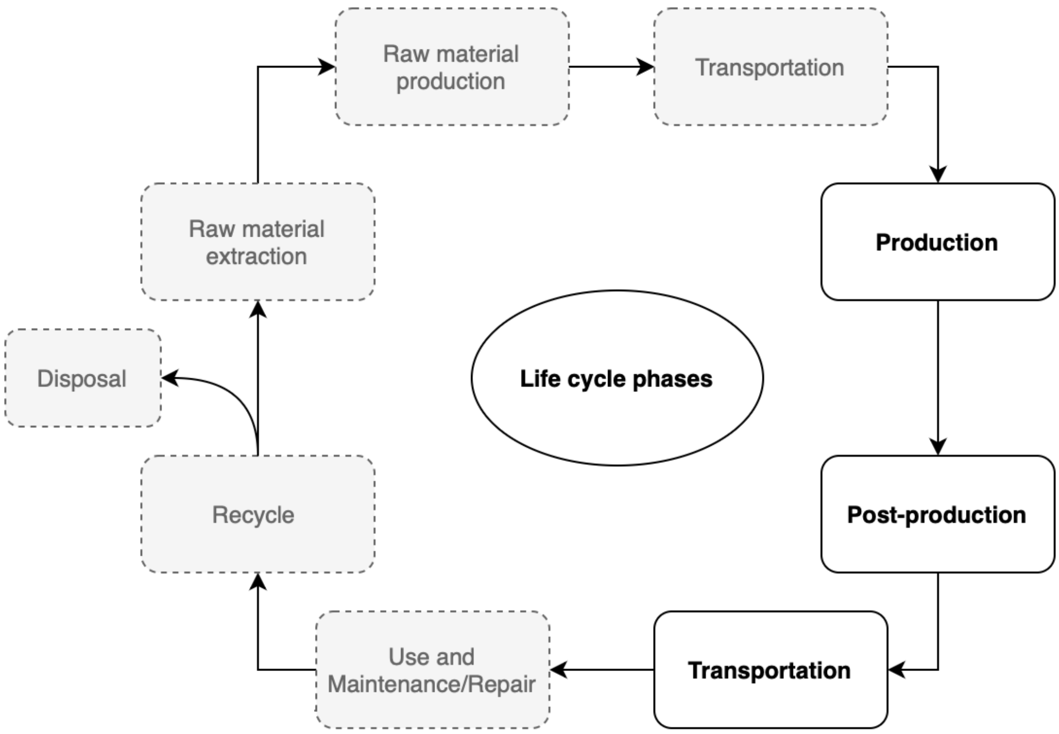

Figure 4: Illustration of the control volume

The control volume used as the framework for this thesis is illustrated in Figure 4. The transportation phase between raw material production and production is also excluded from the control volume. The reason for this is based on the same arguments as excluding the other phases, even though this phase may change when different locations are evaluated. If the scenario is set to be off-site instead of on-site, the transportation mode and distance to send the materials will be different. However, since this research is not based on or has a starting point, the placement of raw material production can be closer or further to the destination of the production. For this study, the assumption is that every spar part production facility chose a producer of raw material as closely as possible. With this assumption, the distance can be seen as "equal" for every scenario and will cancel each other out when comparing on-site and off-site.

We are now left with three phases in the control volume: Production, post-production and transportation. For this analysis, the production and post-production phases will be added together in the parametric analysis. As mentioned earlier, the other part of the results from the specialization project was to quantify the values for the phases defined as the control volume. The result for the production phase is displayed in Table 1.

Machine	**Material**	**Energy consumption (kWh/kg)**	**Citation**
MTT SLM 250	316L	23.06-29.44	(Huang et al., 2016)
M3Linear	316L	117.5-163.33	(Huang et al., 2016)
M3 Linear	316L	107.6	(Kellens et al., 2011)

Table 1: Values for the SLM production

This study will use stainless-steel 316L as a reference point for material. Due to the spare part's complexity in design, size and machine, the energy consumption varies greatly, as Table 1 shows (Isasi-Sanchez et al., 2020). The range of energy consumption found in the literature was 23.06-163.3 kWh/kg. To represent this in the parametric analysis, a range of values will also be represented based on these values. For the post-production phase, finding good sources for values is difficult due to the limited studies in the literature. Paris et al. (2016) use milling as a finishing process to improve the surface of the printed part and quantify the process to use the specific energy consumption of 0.219 kWh/cm^3 (Paris et al., 2016). The energy consumption for the production is given in kWh/kg, so by using the density for stainless-steel 316L (8000 kg/m^3), a simple conversion is performed, and we get 27.375 kWh/kg for the post-production phase. This is then combined with the range for the energy consumption for the production phase used in the analysis. The post-production phase is assumed to be performed at the same site as the printing process. This assumption removes the potential of a new transportation phase.

Transportation mode	Fuel	CO_2 emission ($gCO_2/t*km$)
Cargo ship	Residual fuel	14.4
Railway	Diesel fuel	18.9
Road	Diesel fuel	90
Plane	Jet fuel	1050

Table 2: Fuel emission for different means of transportation (Huang et al., 2016)

Table 2 presents the emission intensity for the four transportation modes used in the parametric analysis found in the literature review. The four means of transportation are long-haul diesel trucks, diesel engine railway, air freight, and residual fuel engine cargo ships. In U. S domestic and international freight, these are the most commonly used (Huang et al., 2016). These values are picked explicitly from the referred paper, but it is compared throughout the literature review and therefore assumed to be sufficiently approved. The most used unit for this phase in the literature is $gCO_2/t*km$. In this unit, the "t" is the metric ton of material multiplied by the distance travelled (km). To include these values in the parametric analysis, we need to multiply the weight of the shipped part or parts and add a conversion factor for a ton to kilogram (kg). The transportation phase will only be added to the off-site scenario since the transportation on-site is considered negligible. This will be explained in more detail in the Methodology section.

2.4 AM in supply chains from an environmental point of view

Since the invention of additive production technologies, they have been compared to traditional- and conventional methods. At the start, the comparison focus was centred on the productivity and economic benefits AM could offer (Alexander et al., 1998; Hopkinson & Dickens, 2003; Ruffo et al., 2006). During the last decade, the focus has now slightly shifted and increased to more focus on the sustainability benefits AM offers as well (Boer et al., 2020; DeBoer et al., 2021; Ford & Despeisse, 2016; Liu et al., 2017; Paris et al., 2016). The research has also led to more specific analytic studies of AM technology where the well-known life cycle analysis (LCA) method is used (Cerdas et al., 2017; Hapuwatte et al., 2016; Ma et al., 2018). The LCA is also the basis of the analysis used to define phases in the preliminary study that the thesis has used to define a control volume and framework for performing the parametric analysis. When implementing AM, changes and challenges will naturally occur throughout the supply chain, which has led to the development of new business models to utilize these challenges in a sustainable way (Cardeal et al., 2022; Cardeal et al., 2020; Godina et al., 2020; González-Varona et al., 2020).

In the implementation of AM, Godina et al. (2020) are trying to increase the knowledge of the impact AM has on sustainable business models and evaluate the impact of the different pillars under Industry 4.0. In addition, they investigate models and scales that can be used to evaluate these impacts. The paper indicates that AM makes the production processes more flexible to adapt to the market's needs and streamline several processes in manufacturing enterprises and is now at a turning point to become a viable alternative to conventional production. Cardeal et al. (2020) introduce a new method to conceive, design, and map sustainable business models, the Business Model Canvas for Sustainability (BMCS). This BMCS is used to assess the long-term sustainability effects in a proposed model that will pre-select a selection of business models. Regarding the spare part industry, AM has vast potential due to the on-demand, handles complex and flexible design, and fits small production volumes best. These properties can change the traditional inventory to a digital inventory, where large warehouses can be moved to the cloud as 3D files. Felt Cardeal et al. (2022) researched the change to a digital inventory, and they have introduced a business model to handle the switch to digital inventory with a focus on sustainability. The proposed model has been assessed using the same BMCS method to compare the business model to current practices, which has raised concern for the economic potential of small- and medium-sized enterprises (SMEs) regarding competitiveness against large enterprises. The findings for the environmental aspects are a reduction in raw material use, but a concern is raised for energy consumption which is presented as the most significant contributor to the environmental impact. They suggest using clean power sources like solar panels, which in other words refer to the energy mix used for production, which emphasizes the importance of implementing the energy mix when analysing environmental impact for AM production. Most of the mentioned papers that look into supply chains and business models have focused on large-scale enterprises, which makes it difficult for smaller enterprises to apply. Due to increasing numbers of SMEs, González-Varona et al. (2020) have tried to fill this gap by developing a business model that integrates a digital supply chain for global operating manufacturers and local producers. The model allows SMEs to operate globally with sustainability criteria and simultaneously guarantee a high service level to their customers for the supply of spare parts (González-Varona et al., 2020). One of the most mentioned benefits regarding the implementation of AM is the decentralization of production, leading to minimized transportation and increased service level. In this context, none of the business model-based papers mentioned has considered energy use versus transportation as the thesis aims to do.

During the specialization project, the SLR analyzed forty-one papers evaluating which life cycle phases to use. The selection process was over several stages, but the common denominator was that all had to include life cycle phases, AM technology and be sustainability related. An interesting finding is that only twenty-six of the forty-one papers included the transportation phase. One paper has also chosen to include transportation in every phase instead of having an individual phase (DeBoer et al., 2021). Di and Yang (2021) investigate a new type of supply chain structure called production-inventory-transportation (PIT), which has been enabled due to AM's capability of fabricating with little to no assembly. The PIT structure combines all the included processes in mobile production, meaning the AM technology is mounted on a truck to drive directly to the customer when needed. This PIT structure calculates GHG emissions from the electricity used in production and transportation and then compares this with the traditional manufacturing method. When applied to a real case, the results show the potential to reduce CO_2 emissions, but this is tested for a limited-sized case, and the material used is plastic. Moreover, the results state that transportation emission is significantly lower than the emission from production, which again emphasizes the importance of energy consumption in environmental analyses.

As mentioned, the researcher's focus and interest have shifted towards more sustainability-grounded studies, where methods like life cycle analysis (LCA) are frequently used to map the phases for products. Several papers use different frameworks to do the LCA. Hapuwatte et al. (2016) use the Product Sustainability Index (ProdSI) framework to give a holistic sustainability analysis that covers the entire life cycle, which they state was lacking in the literature at that time (2016). The framework is thorough and considers the three pillars of sustainability, also called the triple bottom line: economic, environmental and societal, related to the intertwined manufacturing elements: products, process and system levels. The results from case studies using this framework are compared with CM products, indicating that AM products can be more sustainable than CM products for complex geometrical products (Hapuwatte et al., 2016). One major drawback of ProdSI is the inability to include the production quantity as a factor, which directly influences the score and, thus, the sustainability of the products. This is one of the factors included in the analysis for the thesis, which is essential for the production and transportation phases.

Rupp et al. (2022) aim to compare the subtractive and additive production of metal parts by calculating the carbon emissions produced during production and the transportation ways. They also use a decentral production perspective comparable to off-site production, and the values collected for the research are done by a literature review. This research shows that the main drivers are not transportation but the buy-to-fly ratio and the energy mix. This research is highly comparable to the present study, with the same parameters (production and transport) and using the same transport modes (ship, train, truck and planes) and energy mix as a factor in the carbon emissions calculations. The difference is the comparison to the subtractive production instead of on-site AM. Due to the comparison of different production methods (AM and CM), more phases are included in the calculations than in the thesis. Rupp et al. (2022) point out that there is a need for further research on the carbon emission relevance of AM on production and its supply chain, which is close to what this thesis intends to investigate.

With sustainability in mind, the general perception after reading literature related to AM and sustainability is that you either analyze an AM-specific technology in detail or analyze AM and then compare it with CM. In general, the result when comparing the AM and CM is that with some limitations (especially high production volumes), AM is more sustainable than CM. With this general perception, the natural step forward is to look closer into the possibilities and challenges AM technology brings. This thesis will contribute new knowledge to the literature and can act as decision-making support when choosing the location of spare part production.

3 Methodology

This thesis aims to find the most sustainable way to produce spare parts and, with this result, give a decision support system (DSS) for managers and practitioners when choosing a spare part supply chain (SC). The two SC options investigated in this thesis are on-site or off-site production. A mathematical model is developed to determine which SC design is most suitable for specific scenarios. A decision tree is produced from the mathematical model and parametric analysis results to produce the proposed DSS.

The Methodology section is divided into three sub-sections. In Subsection 3.1, the mathematical model is developed to calculate the emissions and compare scenarios to find which SC design (on-site or off-site) has the lowest total emission. Subsection 3.2 present the parametric analysis and how the analysis has produced over 100,000 scenarios to analyze. Finally, Subsection 3.3 explains how the decision tree is created using a decision tree algorithm trained by the result from the parametric analysis. The DSS is the decision tree created and further explained in the Results and discussion section.

3.1 Mathematical model

The mathematical model is developed to compare the emissions of the two SC options. The model has two main parts, one for selecting the number of parts based on an economic assessment and the other for calculating the emission for on-site and off-site production scenarios.

Input parameter	**Description**	**Unit**
T	Time period	Time
h	Holding rate	
MTTF	Mean time to failure	Time
λ	Failure rate	Unit/time
c_b	Unitary backorder cost	Euro/unit
c_p	Unitary production cost	Euro/unit
$\mathrm{L_{on}}$	Leadtime on-site	Time
$\mathrm{L_{delta}}$	Leadtime off-site	Time
E_c	Energy consumption in production	kWh/kg
Dist	Distance from site to costumer	Km
T_{mode}	Transportation mode	gCO_2/ton*km
$\mathrm{Energy_{on}}$	Energy-mix on-site	gCO_2/kWh
$\mathrm{Energy_{off}}$	Energy-mix off-site	gCO_2/kWh
Part size	The size of the part	Kg
S	Order-up-to level	Unit
Constrains		
S_{max}	Maximum order-up-to level	Unit

Costs		
C_h	Holding cost each time unit	Euro/time
C_b	Backorder cost each time unit	Euro/time
C_p	Production cost each time unit	Euro/time

Table 3: Decision variables, constraints, costs and input parameters for the mathematical model

The first part of the model is developed to calculate the number of parts (S) to order based on minimizing the cost, also called an inventory management system (IMS). This part of the model is inspired by Sgarbossa et al. (2021) and Babai et al. (2011). Their implementation of evaluating scenarios to decide the order-up-to level is limited to resemble the applications for a limited storage capacity. The implemented part of this model is a simplified version to cover its function and nothing more. Table 3 lists the system decision variables, constraints, costs and input parameters for the IMS. To simplify the model, the element of part size and complexity is removed, meaning that the unitary backorder cost and the unitary production cost are fixed. Equation 1 (Eq. from now) shows that failure rate (λ) is calculated with the mean time to failure (MTTF). In the simplification of the model, the MTTF is chosen to be constant, which also makes λ constant.

$$\lambda = \frac{1}{MTTF} \tag{1}$$

The Poisson distribution function is used to model the demand due to the fit with the accelerated test used for getting the reliability data. The system is periodic with the demand of ($T+L_i$) periods. The lead time is divided between on- and off-site, where L_{off} has calculated the like Eq. 2 illustrates.

$$L_{off} = L_{on} + L_{delta} \tag{2}$$

Given the stochastic demand y, number of part (S_i) is optimized following Eq. 3-7.

$$min\, C_{tot} = min\, (C_h + C_b + C_p) \tag{3}$$

$$min\, h \cdot c_{P,i} \cdot \sum_{y=0}^{S_i-1} (S_i - y) \cdot P_{\lambda_i, T+L_i, y} + c_b \cdot \sum_{y=S_i+1}^{\infty} (y - S_i) \cdot P_{\lambda_i, T+L_i, y} + \lambda_i \cdot c_{p,i} \tag{4}$$

$$P_{\lambda_i,T+L_i,y} = \frac{\left(\lambda_i(T+\ L_i)\right)^y e^{-\lambda_i(T+\ L_i)}}{y!} \qquad i = 1,\dots,n \tag{5}$$

$$0 \leq S_i \leq S_{max} \tag{6}$$

$$S_i \in\ \mathbb{N} \tag{7}$$

The time unit cost is minimized in Eq. 3, where C_h is the holding cost for the parts, C_b is the backorder cost and is placed every time the demand exceeds the parts in stock. C_p is the production cost. Eq. 4 rewrite Eq. 3 to a more detailed display, where C_h is replaced by $\sum_{y=0}^{S_i-1}(S_i - y) \cdot P_{\lambda_i,T+L_i,y}$ which is the average of parts in stock for period $(T + L_i)$, and when multiplied with $h \cdot c_{P,i}$ (holding cost). C_b is replaced by $\sum_{y=S_i+1}^{\infty}(y - S_i) \cdot P_{\lambda_i,T+L_i,y}$ which is the average of parts in backorder for period $(T + L_i)$, and then multiplied with c_b (unitary backorder cost). The final cost is the C_p (production cost) which is replaced by $c_{p,i}$ (unitary production cost) multiplied by λ_i (failure rate), which gives the expected demand of parts for a period (T). Eq. 5 uses a Poisson distribution to calculate the probability that y numbers of failures occur in the period $(T + L_i)$. The expected demand is $\lambda_i(T + L_i)$. Eq. 6 defines the constraints, and Eq. 7 define S_i as discrete. In the inventory management system part of the model, the part size is chosen dependent on the lead time on-site due to illustrating longer production time for larger parts. The three lead times on-site: 0.1, 0.2, and 0.4, are equivalent to part size: small (0.8 kg), medium (4 kg) and large (8 kg). These part sizes are also equivalent to the lead time off-site, but since the off-site lead time is calculated out of on-site lead time, as Eq. 2 shows, the size of the part(s) is determent out of the on-site lead time. This is used in the emission calculation part of the model, which is described next.

The calculations for the total emission for on-site production and off-site production are displayed in Eq. 8-13:

$$CO_2on = Production\ emission \tag{8}$$

$$CO_2off =\ Production\ emission + Transportation\ emission \tag{9}$$

$$CO_2on = E_c \cdot S_i \cdot part\ size\ \cdot energy_{on} \tag{10}$$

$$CO_2off = E_c \cdot S_i \cdot part\ size\ \cdot energy_{off} + Dist \cdot T_{mode} \cdot S_i \cdot part\ size \cdot \frac{1}{1000} \qquad 11$$

$$Production\ emission = \ E_c \cdot S_i \cdot part\ size\ \cdot energy\ mix \qquad 12$$

$$Transportation\ emission = \ Dist \cdot T_{mode} \cdot S_i \cdot part\ size \cdot \frac{1}{1000} \qquad 13$$

$$Dist \cdot T_{mode} \cdot S_i \cdot part\ size \cdot \frac{1}{1000} = km \cdot \frac{gCO_2}{ton \cdot km} \cdot kg \cdot \frac{ton}{kg} = gCO_2 \qquad 10$$

Eq. 8 and 9 show the general approach to calculate the emission for on- and off-site production and are rewritten in Eq. 10 and 11 to show the input parameters used. E_c is the energy consumption for the production, including the post-production processes. E_c is then multiplied with S_i, which comes from the cost calculations in Eq. 3-7., where the $part\ size$ is also calculated from. Lastly, the energy mix is multiplied with E_c, S_i, and $part\ size$ to get a location-dependent emission for production. For the off-site production, we add the transportation emission to the production emission, as displayed in Eq. 9. The transportation emission uses some additional parameters, $Dist$ is the distance from the spare part production to the customer multiplied by T_{mode}, which is the transportation mode used for transportation. Then multiply with the spare part size ($part\ size$) to add the weight per part transported and finally multiply this with S_i to get the actual weight for the whole shipment. Due to the units in the parameters used, a conversion factor is used. This is displayed in Eq. 14.

3.2 Parametric analysis

As mentioned, we aim to provide managers and practitioners with a DSS to support them when choosing the design of their SC (location). This DSS is presented as a decision tree for visual and factual guidance. When producing this decision tree, the decision tree algorithm requires a dataset to categorize the scenarios into different classes. For this reason, we developed a mathematical model to calculate emissions and then did a parametric analysis, resulting in 105,840 unique scenarios. Table 4: Parameters and values used in the model displays the parameters and values used, except the number of parts (S_i) per order-up since this is calculated in the IMS part of the model and not manually typed in.

Input parameter	Values	Source
T	8	(Sgarbossa et al., 2021)
h	0.0058	(Sgarbossa et al., 2021)
MTTF	91	(Sgarbossa et al., 2021)
c_b	26000	(Sgarbossa et al., 2021)
c_p	750	(Sgarbossa et al., 2021)
L_{on}	0.1;0.2;0.4	(Sgarbossa et al., 2021)
L_{delta}	1;2;3;4	(Sgarbossa et al., 2021)
E_c	20;60;100;140;180	(Huang et al., 2016)
$Dist$	200;2050;3900;5750;7600;9450;11300;13150;15000	Author´s experience
T_{mode}	14.4;18.9;90;1080	(Huang et al., 2016)
$Energy_{on}$	50;150;250;350;450;550;650	(Ritchie et al., 2022)
$Energy_{off}$	50;150;250;350;450;550;650	(Ritchie et al., 2022)
Part size	0.8;4;8	(Sgarbossa et al., 2021)

Table 4: Parameters and values used in the model

When considering different values for the parameters, by testing and failing, the distance and energy mix seemed to have the most influence on the results, which is supported by Rupp et al. (2022) and Di and Yang (2021). Due to this, more values are added to the range for these parameters resulting in a more detailed DSS. For the same reason that some parameters have a more significant influence on the DSS, others influence minimal. This is further discussed in the Results and discussion section.

3.3 Decision tree

To make the SC design choice as easy as possible, we produce a decision tree for the DSS to guide against the optimal (lowest emission) solution. An algorithm, a supervised classification system technique, generates the decision tree. This technique divides the scenarios into classes based on a given set of attributes. To train the decision tree algorithm (MathLab's classification learner), parametric analysis was used. For each scenario, all the values from the input parameters were given. In addition to this, a final class label was added to the mathematical model to train the decision tree algorithm, what the optimal SC design was and be able to predict it. This final label was a simple comparison of the total emissions from the on-site scenario versus the off-site scenario, with the same attributes, resulting in a zero if the on-site had the lowest emission and one for the opposite. These numbers are replaced by the predicted SC design in Figure 7 and Figure 8.

The decision tree is made as follows. The root node is the first recursively split in the decision tree, followed by binary subsets (called branches) based on the Gini diversity index (gdi). Eq. 11 shows the calculation behind the gdi, where K represent the number of class labels (in this case, $K = 2$, on-site or off-site), and the probability of choosing the data point for class k is $p(k)$ (Cantini et al., 2022). The purpose of the Gini diversity index is to measure the probability of a given data point from the dataset being wrongly classified when it is randomly chosen (Arena et al., 2022). Being a probability, the gdi value is between 0 and 1. Low probability means that most of the data point of the dataset belongs to a particular class, and when $gdi = 0$, all the data point belongs to one class. For higher probability, the data points are more randomly divided between several classes, and for $gdi = 1$ indicates that the data points are entirely randomly divided between several classes (Cantini et al., 2022).

$$gdi = 1 - \sum_{K=1}^{K} p(k)^2 \qquad 11$$

Every node in the tree generates two branches out of an attribute and its cut point. The aim in these branches is to minimize Eq. 12 and simultaneously identify the split that will provide the split with the highest purity.

$$min\,(\frac{n_{left}}{n} gdi_{left} + \frac{n_{right}}{n} gdi_{right}) \qquad 12$$

In Eq. 12, n represent the total number of data points in the start node, n_{left} represent the number of data points in the new node for the left branch, and the same goes for the right branch, n_{right} represent the number of data points in the new node for the right branch. gdi_{left} and gdi_{right} represent the Gini diversity index for the new node in the left and right branch (Sgarbossa et al., 2021). At the end of the tree, or the end of the last split for every branch, are leaves. Each split in the tree represents a level, a measure of the depth of the tree. When performed, the algorithm produces a tree with a large depth, which is not exceptionally user-friendly in a DSS. To deal with this complex tree, the tree was pruned to reduce the depth. When reducing the depth of a tree, you also reduce the accuracy of the prediction, but on the other hand, you increase user-friendliness. For this case, user-friendliness is prioritized, and therefore some accuracy was sacrificed for a more user-friendly DSS. Three key performance indicators (KPIs) are introduced to the leaves to evaluate the effectiveness of the decision tree predictions. In Eq. 13, the accuracy of the leaves is calculated, which is the first KPI. The accuracy (*a*) is the ratio between the correct number of predictions ($\#correct\ pred_{leaf}$) and the number of predictions for the leaf ($\#pred_{leaf}$). The probability (*p*) for ending at each leaf is calculated in Eq. 14 and is the second KPI. The probability is given by the ratio between the number of elements reaching the leaf given the constraints ($\#pred_{leaf}$) and the total number of elements in the tree ($\#pred_{tree}$). The last KPI present what consequence the wrong choice of location (off-site vs on-site) will have on the CO_2 emission on average, in this case, called the cost (c). The result of Eq. 15 is a mean percentage of the increased CO_2 emission of the wrongly predicted scenarios. This is obtained as the arithmetic mean of the generated increase of CO_2 emission for each wrong prediction.

$$a = \frac{\#correct\ pred_{leaf}}{\#pred_{leaf}} \qquad 13$$

$$p = \frac{\#pred_{leaf}}{\#pred_{tree}} \qquad 14$$

$$c = \frac{\left(\left|\sum_{k=1}^{\#wrong\ pred_{leaf}} \frac{cost\ for\ wrong\ pred_k - cost\ for\ right\ pred_k}{ost\ for\ right\ pred_k}\right| * 100\right)}{\#wrong\ pred_{leaf}} \qquad 15$$

To summarize, first, the development of the mathematical model is explained, which compare the emissions for on-site and off-site production with a range of different parameters (Section 3.1). Then, all the parameters were included in the parametric analysis (Section 3.2) after an internal evaluation and testing were done by the author. The values for each parameter are presented in. These are then joined together through the mathematical model in a parametric analysis, creating 105,840 realistic scenarios to evaluate which SC design is the best. This result was fed into the decision tree algorithm, as described in Section 3.3, the different values for the scenarios are used as input attributes, and the final class label is described as the identifier. The decision to choose on-site over off-site if it has the same CO_2 emission is justified with easier logistics and shorter lead time, which the author assumes that managers and practitioners will use the same arguments.

4 Results and discussion

This section will present and discuss the results from the parametric analysis and the decision tree algorithm. In Section 4.1, the result of the decision tree algorithm is presented and discussed. Section 4.2 discusses the influence each parameter presented in the decision tree has on the SC design choice, and a guide to orient the DSS is given. The final section presents an explanatory case study to better understand how to use the DSS (Section 4.3).

4.1 Decision tree selection

As mentioned in Section 3.3, the aim is to make the DSS user-friendly with the cost of some accuracy. When evaluating how many splits (depth) to use, four different trees were produced as a comparison with the following depths (D_{max}) and accuracies: D_{max} = 3 (90.3%, small tree), D_{max} = 5 (97.1%, medium tree), D_{max} = 9 (99.2%, large tree) and D_{max} = 14 (99.9%, optimized tree). A sensitivity analysis for the accuracy of the trees is displayed in Figure 5, where the red mark represents the chosen depth for the tree used in this thesis. To get the most accurate prediction, the optimized tree would be the best option but also the least user-friendly tree with a D_{max} = 14. This means that there are fourteen splits, with one new constraint to consider for each split. Compared with the large tree, you only lose 0.7% accuracy by pruning down the D_{max} = 9. This tree also has high accuracy (99.2%), with considerably fewer splits and constraints. Even with this reduction in depth, nine is still a large tree that is hard to use for a DSS with a user-friendly focus and is pruned even more to increase user-friendliness. Figure 5 shows that the accuracy drops significantly from D_{max} = 5 to D_{max} = 3. This is where the trade-off between user-friendliness and accuracy starts to tip in favour of user-friendliness, and D_{max} = 3 is therefore seen as not accurate enough for the DSS.

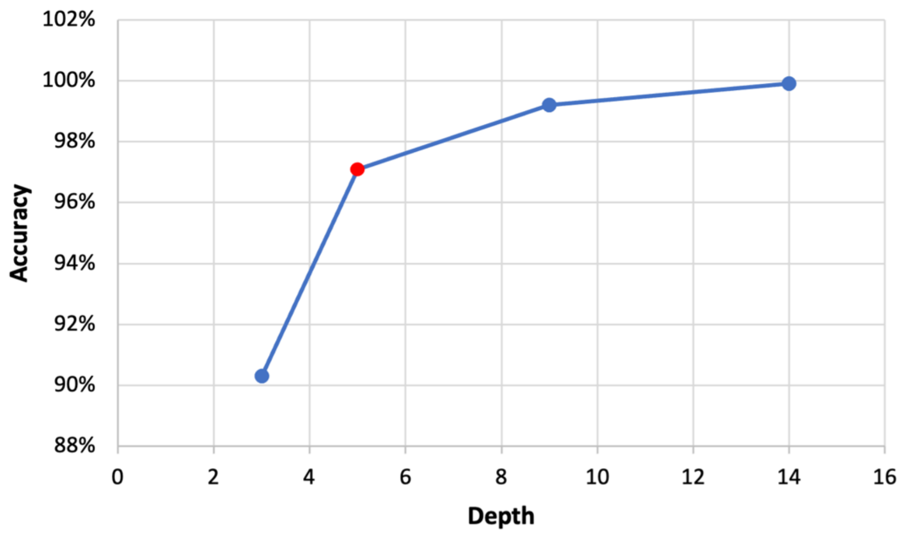

Figure 5: Sensitivity analysis for the accuracy of the decision trees

Another essential aspect when considering the accuracy level is the KPIs (Section 3.3) for the leaves, especially cost (*c*, increase in CO_2 emission for the wrong prediction of SC design), meaning that a high cost should demand a higher accuracy to decrease the risk of ending up with a less sustainable solution. The KPIs show that seven leaves have an accuracy of 100%, and the cost is zero. Regarding the accuracy/cost evaluation, these leaves are less interesting since there is a larger portion with lower accuracy. For these leaves, the cost rate increase is between 5.19% to 134.56%, with a mean increase rate of approximant 36%. Figure 6 represents the two KPIs for the leaves where the accuracy rate and cost rate are compared for the leaves with lower accuracy than 100%. The comparison reveals that leaves with lower accuracy than around 90% tend to have higher costs than those with over 90%, which further means that lower accuracy leads to a higher cost risk if the prediction fails from the chosen SC design. The mean cost rate for these leaves (less than 90 %) is 45.81%. This cost rate is considered high, and high accuracy is therefore required when choosing the depth of the tree to decrease this risk. It further supports the selected tree with associated accuracy. When considering the decision tree as a tool, the excluded leaves with 100% are important to include to give a better perspective for the general effectiveness as a tool. The mean accuracy rate for all the leaves is around 89%, and the cost is around 23%. This is still a high cost to pay if the chosen prediction is wrong, but with an accuracy that is almost 90%, the risk is considered acceptable, with some exceptions. There are some leaves with a high cost ($50\% < c$) combined with low accuracy ($a < 70\%$) that make it too risky to trust the prediction of the tree, this requires additional measures. Consulting a tree with a higher maximum depth will offer higher accuracy, reduce the risk, and verify the DSS prediction.

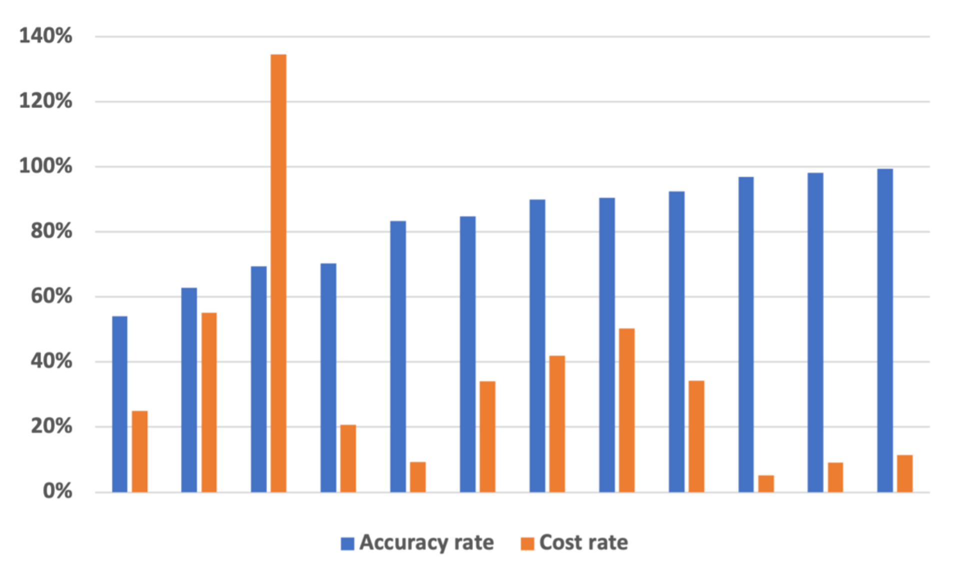

Figure 6: Accuracy compared with cost rate (KPIs for the leaves)

4.2 The influence from the parameters

The decision tree (Figure 7) reveals that some parameters are more important when choosing optimal SC design than others. There are six parameters included in the constraints for the splits in the decision tree: *energy*$_{on}$ (*energy_on), energy*$_{off}$ *(energy_off), transportation mode, E_c, Lead time off-site (*L_{off}*) and Distance.* The further up the tree and the number of times mentioned, the more crucial they are for the SC design choice. It emerges that *energy*$_{on}$ and *energy*$_{off}$ are the two parameters with the most impact on CO_2 emission and the two with the most influence when choosing the optimal SC design. These findings are the same as Rupp et al. (2022) found, that the main drivers are not transportation but the energy mix. As mentioned earlier (Table 3: Decision variables, constraints, costs and input parameters for the mathematical model *energy*$_{on}$ and *energy*$_{off}$ is the energy mix for a given location and will always be different for the on-site and off-site location in the mathematical model made in this thesis. This is not necessarily the case in the real world, where several countries have similar energy mixes. However, this is complex due to the transportation mode and distance related to the calculation. For instance, a slightly lower CO_2 intensity in the energy mix in the closest countries might be enough for a lower total CO_2 emission due to the short distance and the weighting of the energy mix. Another interesting aspect of the parameters represented in the tree is L_{off} and the values used in the split. Lead time off-site is only included in the first part of the mathematical model as described in Section 3.1, which is not the case for the other parameters represented in the tree. The dividing between 1.3 weeks is interesting due to the broad range used in the model (1.1-4.4), but after investigating the parametric analysis, the result of using values under 1.3 is that the re-order quantity (S) for off-site is two and increases to three when lead time is over 1.3. In contrast, the on-site production quantity is two for all values of on-site lead time. This means that most off-site production produces three spare parts, while on-site only produces two. This will further lead to increased CO_2 production compared with on-site production since one more spare part is produced. This also increases transportation emissions since it is based on how many spare parts are being shipped. At the same time, the quantity is based on an optimized quantity based on cost, so it will often be a different quantity for a site based off-site than a close spare part production (on-site) where the lead time is much lower, allowing increasing order frequency instead of ordering larger quantities.

The transportation mode used in the part shipping is also represented in the decision tree, and the choice given in the splits is either using a ship, train or truck, or just a plane. Table 2 reveals that the plane has a significantly higher CO_2 intensity than the three other alternatives, which dramatically impacts the transportation mode as a parameter. Just looking at the values for the transportation alternatives, a plane could have been ruled out when you compare it to the other alternatives, but the ability for rapid shipping over long distances makes the plane a valid choice for many. When using a plane, the focus is not on sustainability but on economic aspects due to the low lead time compared to the other alternatives. Moreover, the transportation mode is multiplied by the distance the spare parts are shipped, and the influence of the distance is also represented in the tree, just as the last split before the leaves. This suggests that the distance does not have the same degree of influence as the transportation mode, which can be explained by the vast distance in values for the transportation mode. At the same time, the two parameters are dependent on each other and, multiplied with the quantity (S) and part size, constitute the transport emission as a whole.

The last parameter mentioned in the decision tree is energy consumption (E_c), which is placed in the same way as distance (the last split before the leaves) and has a minor impact on the SC design choice. The energy consumption is on parameters where the values inside vary a lot, and due to technological development, the values will likely decrease due to more efficient processes. This can have an interesting effect since the split in value for the energy consumption is done in the lowest part of the value range.

In general, the DSS has a higher probability (p) to suggest on-site (6%) production than off-site (4.3%) when looking at the mean for the leaves. This corresponds to the result of the parametric analysis, where only 31.2% of the scenarios resulted in lower carbon emissions for off-site SC design. However, the importance of some parameters can change this. The energy mix is already mentioned as an important parameter, which is confirmed by the fact that it is the first choice in the tree. When choosing less than 300 gCO2/kWh for energy mix off-site changes the number of off-site scenarios in the dataset (parametric analysis results) by 62% in favour of off-site production. Regardless of what is chosen in the first split, both of the following splits (D = 2) give on-site energy intensity options. The energy mix for both SC designs is crucial when choosing the right SC design, and due to this, there are possible to draw some general conclusions or pointers based on this. If the energy mix off-site is lower than 300 (gCO2/kWh) and the energy mix on-site is: (i) lower than 200, the prediction is most likely on-site; (i) equal or higher than 200, the prediction is most likely off-site. If the energy mix (gCO2/kWh) off-site is equal to or higher than 300, the prediction is most likely on-site SC design.

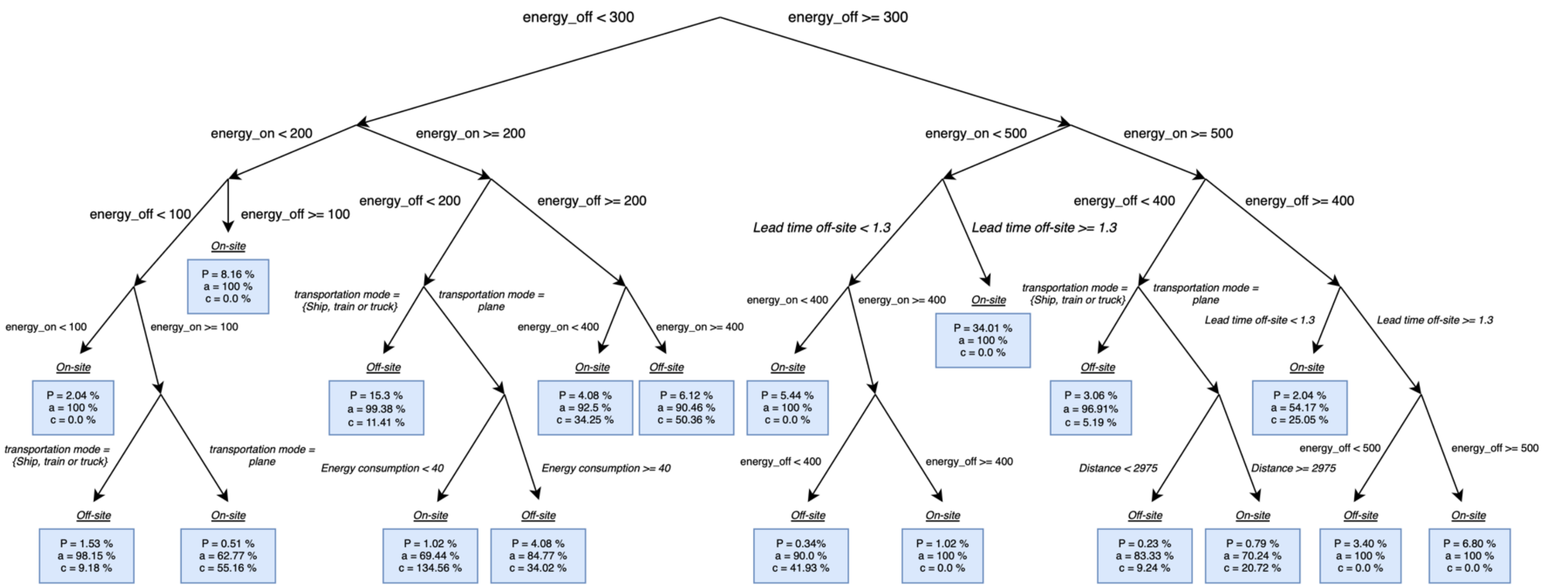

Figure 7: The decision tree with D_{max} = 5, accuracy = 97.1%

With the DSS presented in the form of the decision tree, the actual use for managers and practitioners is not that clearly explained. When using the DSS, the user starts at the top of the tree and has two options to choose between. When finding the right path, the user follows this down to the next split, where two new options exist. This continues down until you reach the end (a leaf), where you have the prediction of which SC design is the most sustainable. When the user is at the leaf, the next step will be to look at the KPIs and, most importantly, the cost (c) and accuracy (a) to evaluate how significant the risk is for choosing wrong. At this point, there are two outcomes detected by the author. Firstly, high accuracy at the leaf relevant for the user means that the prediction can be trusted. Secondly, if the accuracy is lower, the cost should be included in the evaluation to assess the actual risk. If the cost is low, the risk connected to the low accuracy must be evaluated as acceptable. With the high cost and unacceptable risk, a solution could be to consult the more accurate decision trees (D_{max} = 9 and D_{max} = 14) mentioned earlier. To illustrate the use of the DSS, an explanatory case study is presented.

4.3 Explanatory case study

This case study is fiction but with a base of facts due to some known values related to the chosen locations. Regardless of internal spare part production or the customer's location, the on-site values are assumed to be the same for both scenarios. The first part of the mathematical model is not altered from the values set as constant values. To decide the distance between Norway and Italy, the transportation mode is set to $\mathrm{T_{mode}}$ = 90, which means the truck is the chosen mode. Distance by road is approximant 2400 km (Oslo-Bologna) and about 25 hours of driving, which is about 2-3 days equivalent to $\mathrm{L_{delta}}$ = 1 week and further gives $\mathrm{L_{off}}$ = 1.2 weeks. The on-site location is set to Italy, and the off-site is set to Norway. This gives us the exact values for the energy mixes: $\mathrm{Energy_{on}}$ = 226 and $\mathrm{Energy_{off}}$ = 26 (Ritchie et al., 2022). It is important to note that this is for 2021. Italy is a vel developed country, especially in terms of technology, and the energy consumption for the printing machines and post-production processes is therefore set to 35.

Input parameter	**Values**
$\mathrm{L_{on}}$	0.2
$\mathrm{L_{delta}}$	1
$\mathrm{L_{off}}$	1.2
$Dist$	2400
T_{mode}	90
$\mathrm{Energy_{on}}$	226
$\mathrm{Energy_{off}}$	26
E_c	35

Table 5: Input parameters relevant to the DSS explanatory case study

Table 5 displays the relevant parameters and values for the DSS choices. When applying these values to the parameters in the DSS (Figure 7: The decision tree with Dmax = 5, accuracy = 97.1%, the optimal SC design is predicted to be off-site production. The path of choices in the DSS is illustrated in Figure 8: Illustration of choices done in the explanatory case study, with the end leaf coloured in red. The KPIs for the leaf reveal that the prediction accuracy is 99.38%, which means that this prediction is to be trusted. This also confirms the general conclusion or pointer mentioned earlier, where the energy mix off-site is lower than 300 (gCO2/kWh) and the energy mix on-site is higher than 200, the prediction is most likely off-site.

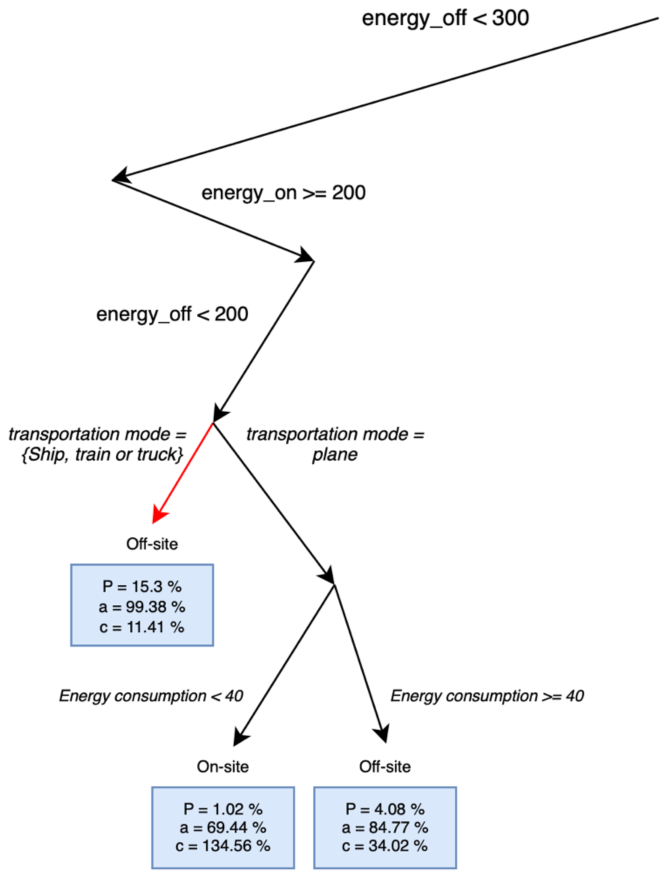

Figure 8: Illustration of choices done in the explanatory case study

An interesting observation of the result is that the transportation mode is an essential factor for this result. If the transportation mode had been a plane instead of a truck, ship or train, the prediction would have been on-site production due to the low production and post-production energy consumption. A plane is often used for shipping spare parts due to often time-sensitive scenarios like production stoppage. This type of scenario is presented by Rupp et al. (2022), where a plane was the only alternative for express deliveries over long distances due to the urgency of the costumer. For managers or practitioners using the DSS, precise information is important to get the best and most realistic prediction possible.

5 Conclusion

This thesis proposes a DSS to guide managers and practitioners in choosing an environmental SC design for spare part production based on their situation. Only two different SC designs are considered in this work, which is on-site and off-site production, with the use of AM as the production method. Three steps were followed to develop such a DSS: (i) A mathematical model with two parts was developed. The first part is a cost calculation to determine the optimal order quantity (one calculation for each SC design) to use in the second part. The second part calculates the total emissions for the two SC designs and then compares them to determine which has the lowest total emission; (ii) 105,840 realistic scenarios were developed through a parametric analysis, where all parameters were included, but some parameters were assigned more values after an assessment by the author that some parameters were more relevant than others. For all the scenarios developed, the optimal SC design (lowest CO_2 emission) was identified using the mathematical model mentioned in (i); (iii) The result of the parametric analysis was used as the dataset in a decision tree algorithm, which produced the DSS. A sensitivity analysis was performed to find the right balance between accuracy (high maximum depth) and user-friendliness (low maximum depth), which was found to be a maximum depth of five levels with an accuracy of 97.1%. There were established three KPIs for each leaf, accuracy (a), probability (p) and cost (c), which revealed that some leaves had low accuracy and others high. The same goes for the cost of the leaves, which is the percentage increase in emission if the prediction in the tree was wrong. A comparison between the cost and accuracy revealed that leaves with lower accuracy than around 90% tend to have higher costs than those with over 90%, which further means that lower accuracy leads to a higher cost risk if the prediction fails from the chosen SC design. The cost is high, but with the high accuracy for the tree and generally high accuracy for the leaves, the risk of increased cost for managers and practitioners is considered acceptable. Therefore, the DSS is seen as a robust tool in decision support since it selects the optimal SC design with a very low risk of the additional cost.

There are not found any similar studies in the literature with the same aim and focus provided by the literature, and especially no DSS tool for managers and practitioners for choosing optimal SC design for minimizing the environmental footprint. For this study, a decision tree algorithm is used since it consists of an easy-to-use tool with a tree-like model of decisions, which is designed as a set of logical rules describing the decision criteria (Arena et al., 2022). Moreover, the decision tree provides KPIs to make the predictions easier to assess regarding the risk of extra cost. In the development of the DSS, fourteen parameters (T, h, MTTF, c_b, c_p, $\mathrm{L_{on}}$, $\mathrm{L_{delta}}$, E_c, $Dist$, T_{mode}, $\mathrm{Energy_{on}}$, $\mathrm{Energy_{off}}$, $\mathrm{Part\ size}$) was used as input, another two parameters (S and $\mathrm{L_{off}}$) is generated in the calculations carried out in the mathematical model. The decision tree revealed that some parameters were more important than others. The energy mix for both SC designs is the two parameter with the greatest influence on the SC design choice. The results reveal that it is possible to make some general outcomes (with some uncertainty, but with an overwhelming probability):

- With an energy mix (gCO_2/kWh) for off-site production lower than 300 and an energy mix lower than 200, the prediction is on-site. If the energy mix on-site is higher than 200, the prediction is off-site.
- Conversely, the prediction is on-site if the energy mix off-site is higher than 300.

5.1 Limitations and future research

Since this study has used the specialization project as a base, some limitations are carried forward and may impact this study. Three main limitations were put forward: (i) During the SLR, only one database was used to collect relevant papers; (i) When searching, a set of keywords was used that naturally had some limitations in addition to its function; (iii) The SLR was performed early February 2022. These limitations may mean that new or relevant articles have been omitted, which for this study means that the values picked for some parameters are missing to cover all possibilities. Regardless, a range of values is established for parameters where the literature is inconsistent.

There are several assumptions made to make this study easier to handle and comply with formulas and models. To simplify the first part of the mathematical model, the element of part size and complexity is neglected, meaning that the unitary backorder cost and the unitary production cost are fixed. Moreover, the MTTF is chosen to be constant, which also makes λ constant. This was done to make the parametric analysis easier to run, and since the first part is small compared with the second, it did not have a major impact on the result. However, this could be extended into the model for a more nuanced picture. Some assumptions were made to create a control volume: (i) Every spar part production facility chose a raw material supplier as closely as possible. With this assumption, the distance can be seen as "equal" for every scenario and will cancel each other out when comparing on-site and off-site; (ii) The post-production phase is assumed to be performed at the same site as the printing process. This assumption removes the potential of a new transportation phase.

Since this is the first study of its kind, there are several opportunities to develop this study in the future further. Here are some suggestions:

- Rapid development in technology and the sustainable focus worldwide will affect the values and inputs in the near future, which makes a re-do of the study with updated values and insight to compare to the current study.
- Some of the assumptions in the mathematical model could be adjusted since their intended function was to simplify the model, which means that several assumptions can be relaxed, and some input parameters can be increased. MTTF, c_b and c_p are all fixed costs that can be expanded or adjusted to adapt the tool for a larger user market.
- Another possible development could be to expand the first part of the mathematical model to be a fully integrated cost part, where an SC design of optimized sustainability and profit could be developed and included in the DSS.

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Appendix

Appendix A - SLR result

Placed on the next page due to the orientation of the table.

Citation	Title	Raw material extraction	Raw material production	Transportation	Production	Post processing stages	Use	Maintenance/repair	recycling	Disposal
(Raoufi et al., 2022)	Cost and environmental impact assessment of stainless steel microscale chemical reactor components using conventional and additive manufacturing processes		x		x					
(Gao et al., 2021)	Eco-friendly additive manufacturing of metals: Energy efficiency and life cycle analysis	x	x	x	x	x	x		x	
(DeBoer et al., 2021)	Additive, subtractive, and formative manufacturing of metal components: a life cycle assessment comparison		x	x	x		x		x	
(Liao & Cooper, 2020)	The environmental impacts of metal powder bed additive manufacturing		x		x	x	x		x	
(Serra et al., 2021)	Comparing environmental impacts of additive manufacturing vs. Investment casting for the production of a shroud for gas turbine	x	x	x	x	x				
(Di & Yang, 2021)	Greenhouse gas emission analysis of integrated production-inventory-transportation supply chain enabled by additive manufacturing	x	x	x	x					
(Lyons et al., 2021a)	Environmental impacts of conventional and additive manufacturing for the production of Ti-6Al-4V knee implant: a life cycle approach	x	x		x	x			x	
(Yao et al., 2019)	Life cycle assessment of 3D printing geo-polymer concrete: An ex-ante study		x	x						

(Mele et al., 2020)	Life cycle impact assessment of desktop stereolithography	x	x	x	x	x				
(Yosofi et al., 2019)	Additive manufacturing processes from an environmental point of view: a new methodology for combining technical, economic, and environmental predictive models				x	x				
(Feldmann et al., 2019)	Strategically Aligning Additive Manufacturing Supply Chains for Sustainability and Effectiveness		x	x	x	x	x	x	x	x
(Fredriksson, 2019)	Sustainability of metal powder additive manufacturing	x	x	x	x				x	
(Yao & Huang, 2019)	A parametric life cycle modeling framework for identifying research development priorities of emerging technologies: A case study of additive manufacturing		x	x	x			x		
(Priarone et al., 2019)	A modelling framework for comparing the environmental and economic performance of WAAM-based integrated manufacturing and machining		x		x	x				
(Liu et al., 2017)	Comparative study for environmental performances of traditional manufacturing and directed energy deposition processes	x	x	x	x	x				
(Liu et al., 2018)	Investigation of energy requirements and environmental performance for additive manufacturing processes	x	x		x					

(Ma et al., 2018)	An exploratory investigation of Additively Manufactured Product life cycle sustainability assessment	x	x	x	x	x	x	x	x	x
(Peng et al., 2018)	Sustainability of additive manufacturing: An overview on its energy demand and environmental impact	x	x	x	x	x	x		x	x
(Yosofi et al., 2018)	Framework to Combine Technical, Economic and Environmental Points of View of Additive Manufacturing Processes				x	x				
(Mami et al., 2017)	Evaluating Eco-Efficiency of 3D Printing in the Aeronautic Industry			x	x		x	x	x	
(Walachowicz et al., 2017b)	Comparative Energy, Resource and Recycling Lifecycle Analysis of the Industrial Repair Process of Gas Turbine Burners Using Conventional Machining and Additive Manufacturing				x		x		x	x
(Cerdas et al., 2017)	Life Cycle Assessment of 3D Printed Products in a Distributed Manufacturing System		x	x	x		x			x
(Fratila & Rotaru, 2017)	Additive manufacturing-a sustainable manufacturing route	x	x	x	x	x	x		x	x
(Nagarajan & Haapala, 2017)	Environmental Performance Evaluation of Direct Metal Laser Sintering through Exergy Analysis	x	x	x	x				x	
(Kellens et al., 2017)	Environmental Impact of Additive Manufacturing Processes: Does AM Contribute to a More Sustainable Way of Part Manufacturing?		x		x	x				

(Minetola & Eyers, 2017)	Additive manufacturing as a driver for the sustainability of short-lifecycle customized products: The case study of mobile case covers		x	x	x				x	x
(Kafara et al., 2017)	Comparative Life Cycle Assessment of Conventional and Additive Manufacturing in Mold Core Making for CFRP Production		x		x	x			x	x
(Ford & Despeisse, 2016)	Additive manufacturing and sustainability: an exploratory study of the advantages and challenges	x	x		x	x	x	x	x	x
(Huang et al., 2016)	Energy and emissions saving potential of additive manufacturing: the case of lightweight aircraft components	x	x	x	x	x				
(Freitas et al., 2016)	Sustainability in extrusion-based additive manufacturing technologies			x	x		x		x	x
(Hapuwatte et al., 2016)	Total Life Cycle Sustainability Analysis of Additively Manufactured Products				x	x				
(Paris et al., 2016)	Comparative environmental impacts of additive and subtractive manufacturing technologies			x	x	x	x		x	x
(Lachmayer, 2015)	Approach for a comparatively evaluation of the sustainability for additive manufactured aluminum components	x	x	x	x	x				
(Despeisse & Ford, 2015)	The role of additive manufacturing in improving resource efficiency and sustainability		x		x		x	x	x	x

(Burkhart & Aurich, 2015)	Framework to predict the environmental impact of additive manufacturing in the life cycle of a commercial vehicle	x	x		x	x	x		x	x
(Faludi et al., 2015)	Comparing environmental impacts of additive manufacturing vs traditional machining via life-cycle assessment			x	x					x
(Catriona, 2014)	The potential of 3D printing to reduce the environmental impacts of production	x	x	x	x		x		x	x
(Gebler et al., 2014)	A global sustainability perspective on 3D printing technologies		x	x	x		x		x	x
(Le Bourhis et al., 2014)	Predictive model for environmental assessment in additive manufacturing process		x	x	x				x	
(Kreiger & Pearce, 2013)	Environmental life cycle analysis of distributed three-dimensional printing and conventional manufacturing of polymer products	x	x	x	x	x				
(Rickenbacher et al., 2013)	An integrated cost-model for selective laser melting (SLM)				x	x				

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