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Feasibility and suitability analysis of additive manufacturing in pre-conceptual design phase

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ABSTRACT
The application of additive manufacturing (AM) has expanded beyond prototyping, offering unique opportunities compared to conventional manufacturing methods such as casting and machining. To fully utilise these opportunities, products must be designed specifically for AM. Therefore, it is important to determine not just *how to design for AM*, a topic which has been studied extensively, but also *when to design for AM*, a topic which remains under-explored. We therefore posit that this can be solved by providing designers with a clear set of guidelines to help them determine when AM is the appropriate choice. This, in turn, can accelerate the industrial adoption of AM while also enabling more effective and efficient production processes. This paper introduces a method to support decision-making by assessing the feasibility and suitability of AM in comparison to other manufacturing processes in the early design phase. The proposed method offers a structured and transparent guideline, distinguishing it from existing approaches in the literature. Finally, an example illustrating how this method can guide design decisions effectively is presented, fostering a more informed and strategic approach to the adoption of AM in industry.

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Engineering design; additive manufacturing; decision making; early design; feasibility and suitability analysis

Acronyms

AHP analytic hierarchy process AI artificial intelligence AM additive manufacturing CM conventional manufacturing DfA design for assembly DfAM design for additive manufacturing DfM design for manufacturing DfX design for X LCA life cycle assessment MCDM multi-criteria decision making ML machine learning MPDS manufacturing process decision support TOPSIS technique for order of preference by similarity to ideal solution

1. Introduction

In recent decades, the application of additive manufacturing (AM) has moved rapidly from being a prototyping tool to a production method (Thompson et al. 2016). The growing interest in AM is often attributed to two factors. First, modern manufacturing paradigms such as Industry 4.0, integrated with technologies such as AM, have created the possibility of value chains that are far more efficient and effective (Alcácer and Cruz-Machado 2019).

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Second, due to its additive nature, the technology itself promises greater design flexibility than was previously possible with traditional methods (Brahma and Wynn 2020). As a result, industries stand to gain significantly from its appropriate use.

Although there has been significant interest, the industrial uptake has been slow (Kulkarni et al. 2021; Martinsuo and Luomaranta 2018). One key barrier is the lack of research examining AM's position in the overall product and process cycles (Mallalieu et al. 2022; Martinsuo and Luomaranta 2018). This is an important factor to consider since it determines how much of the advantages offered by AM can actually be realised. For instance, design for additive manufacturing (DfAM) guidelines emphasise the need to consider AM-specific design constraints from the outset (Diegel, Nordin, and Motte 2019). This is particularly problematic for companies that incorporate both AM and traditional manufacturing methods in their portfolio (Page, Yang, and Zhao 2019). Designers must decide whether to choose AM or another method, even before design concepts are generated – when there is hardly any information available about the product (Chandrasegaran et al. 2013; Douglas C. Eddy, Krishnamurty, and Steudel 2019). However, the current state of practice is in contravention to this, i.e. design prerequisites are created first before any significant exploration of alternative manufacturing methods is undertaken. In certain cases, however, adopting AM early in the process can be beneficial, for instance, in the production of spare parts to enhance efficiency and reduce lead time. For scenarios where the suitability of AM is less evident, structured guidelines are essential to support informed decision-making.

To make decisions about the suitability of AM, designers are forced to rely on heuristics or experience, which often produces suboptimal results. In this paper, this gap is addressed, i.e. a lack of systematic method to derive sufficiently adequate design preconditions that enable robust designs tailored to additive manufacturing in the pre-conceptual design phase. Further, a structured method is proposed to assist feasibility and suitability analysis of AM in the early design phase. For this purpose, three research questions are formulated and addressed in the following article:

RQ1: What key factors available in the pre-conceptual design phase determine the suitability of AM?

RQ2: How can these factors be integrated into a method to guide designers in evaluating the feasibility and suitability of AM before design commences?

RQ3: What are the benefits and limitations of the proposed method?

The rest of the paper is structured as follows: Section 1 explores the background and challenges of industrial adoption of AM, highlighting gaps in existing methods for assessing feasibility and suitability. Section 2 presents the influencing factors affecting these decisions, forming the foundation for the introduction of the manufacturing process decision support (MPDS) method in Section 3. Section 4 demonstrates the application of this method, while in Section 5 the research questions are answered and discussed, including the key insights. The paper is concluded in Section 6.

2. Background

The strong interest in AM stems primarily from the potential advantages it offers (Ford and Despeisse 2016). A key benefit is the tool-less nature of the fabrication process (Baumers et al. 2016), which in turn opens up many possibilities. For example, the lack of a requirement for tooling results in greater flexibility in producing complex geometries (Diegel, Nordin, and Motte 2019; Thompson et al. 2016). Additionally, it enables a highly flexible production system, significantly streamlining supply chains, reducing lead times and lowering transportation costs (Afshari, Searcy, and Jaber 2020; Rinaldi et al. 2021). However, despite many predictions of high growth, the uptake of AM has only been modest (Attaran 2017; Ronchini, Moretto, and Caniato 2023).

2.1. Challenges surrounding industrial adoption of AM

Researchers point to several challenges that hinder the rapid adoption of AM, particularly by large companies. While the potential of AM is well understood, awareness of how to realise its benefits and the obstacles and constraints to overcome remains limited. This lack of clarity is common for any novel technology undergoing industrialisation, as seen in the Gartner Hype Cycle, which describes a typical drop in interest (trough of disillusionment) following the slope of enlightenment as industries face the learning curve associated with implementing new technologies (Gartner Inc. 2023). Compared to traditional manufacturing methods, AM is still in its nascent stages (Campbell et al. 2023), which often leads to scepticism, especially concerning the production of final parts. Spallek and Krause (2017) surveyed more than 172 industry designers and found that, despite high interest, noted a degree of scepticism about using AM for end-user parts. A primary challenge cited was the lack of decision support in existing DfAM methods, particularly concerning AM-specific impacts, requirements and constraints that designers must consider. Similar challenges have been observed for different contexts by Omidvarkarjan et al. (2023), Ahuja, Karg, and Schmidt (2015), Ituarte, Khajavi, and Partanen (2016), and Mellor, Hao, and Zhang (2014), among many others.

The following section discusses some of these challenges in detail. Section 2.2 discusses the challenges with regard to the available DfAM methods. This is followed by a discussion and gap analysis on traditional and AM-specific decision supports in Sections 2.3–2.6. A summary of the identified gaps is provided in Section 2.7.

2.2. Design for additive manufacturing (DfAM)

Similar to design for manufacturing (DfM) and design for assembly (DfA) (Boothroyd 1994) which are used in the context of traditional manufacturing and assembly methods, DfAM presents guidelines specifically tailored to AM (Thompson et al. 2016). DfAM methods aim not only to assist designers in successfully printing parts but also to maximise the advantages that AM offers. While AM approaches help overcome adoption barriers, they also introduce significant challenges, as discussed below.

For instance, the design freedom provided by AM allows designers to relax many of the constraints imposed by traditional manufacturing methods. However, this freedom comes with new constraints (Borgue et al. 2019; Diegel, Nordin, and Motte 2019), such as restricted overhang angles and the requirement for support structures. Furthermore, the cost-benefit ratio of AM compared to traditional methods is not always immediately apparent based on DfAM alone (Li et al. 2020). While AM can simplify the supply chain and reduce certain costs, it may also increase lead times due to various reasons. For instance, in high-performance metal parts, the qualification process is complex due to the risks of defects generated during AM processes, requiring more complex post-processing and qualification procedures compared to other manufacturing methods such as forging (Sanaei and Fatemi 2021).

Another factor in the slow adoption of AM is the cognitive challenge it poses, as highlighted by researchers such as Seepersad (2014). Designers often struggle to adapt to the new way of thinking required for AM. Familiarity with traditional manufacturing may inhibit willingness to explore solutions that fully utilise the capabilities of AM (Richter et al. 2018). Therefore, transitioning to AM requires practice and a fundamental shift in design thinking (Thomas-Seale et al. 2018). Moreover, existing DfAM methods do not account for variations in experience and knowledge levels among designers, which further hinders adoption (Spallek and Krause 2017).

2.3. *Elimination based decision support*

Several methods are available in the literature that facilitate the selection of manufacturing processes and technologies, with a specific focus on traditional manufacturing methods (see reviews by Hamzeh and Xu 2019; Khaleeq uz Zaman et al. 2016). Most of these methods are driven primarily by two general requirements; first, the material selection must satisfy the design requirements, which in turn determines a feasible production process. Second, the selection of the production process must be cost- and time-efficient (Liu, Zhu, and Ye 2020).

Lovatt and Shercliff (1998) for instance, proposed a two-phase approach for selecting manufacturing processes. The first phase involves the identification of objectives and requirements of the product, while the second phase includes technical and economic evaluation to screen out irrelevant and infeasible processes. As another example, Swift and Booker (2013) introduced a method that begins with selecting materials that conform to the design specifications, discarding all others. In the next step, based on a matrix of annual production quantity and material, possible manufacturing methods are chosen. The authors then suggest considering broader engineering and economic aspects to make a final selection of the manufacturing method. Another popular method based on material selection is by Ashby (2005). The method enables users to relate different material properties to various product requirements to select feasible material options. The material selection is then extended to the manufacturing process selection method that relates product function and requirements to material and manufacturing constraints, reaching a set of feasible manufacturing options. Similar approaches can be found in studies conducted by Chen et al. (1995), Smith and Rennie (2008), Kumar and Singh (2007), and Van Kesteren, Jan Stappers, and De Bruijn (2007).

These methods share a common structure, beginning by defining objectives and product requirements and then screening out infeasible material and manufacturing alternatives based on constraints, further refining the design as it progresses. Ultimately, they select the most suitable combination of materials and manufacturing processes. While the approach of screening out infeasible options and leaving feasible alternatives to last as long as possible works in cases of traditional manufacturing processes, it limits the potential benefits of different DfAM guidelines. Further, these methods do not adequately address AM as a production manufacturing method. Swift and Booker (2013), for instance, still consider AM as a rapid prototyping technology rather than a manufacturing method for production. This implies a lack of guidance on designing with AM, limiting the potential to leverage its benefits effectively.

Another criticism of these methods originates from the relatively small number of factors they consider. Some methods, such as Swift and Booker (2013), which suggest multiple process drivers, depend on logical reasoning to eliminate infeasible options, rather than providing guidelines for the suitability analysis of different manufacturing process alternatives. Consequently, multi-criteria decision making (MCDM) techniques have been developed for process selection, focussing on selecting the best alternatives rather than eliminating options. The following section discusses a selection of MCDM-based methods.

2.4. General multi-criteria decision support methods

When selecting a suitable manufacturing process, various factors must be considered, often diverse and potentially conflicting. multi-criteria decision making (MCDM) is a widely used umbrella term for methods which typically operate in three phases. First, important criteria are identified. Second, alternative manufacturing methods are identified. Third, each of the alternative manufacturing methods is evaluated against the criteria, and the alternatives are ranked. The selection of the best alternative is typically determined using techniques such as analytic hierarchy process (AHP) or technique for order of preference by similarity to ideal solution (TOPSIS) (Liu, Zhu, and Ye 2020). AHP performs a pairwise comparison of criteria (Saaty 1980), while TOPSIS assesses the distance of various alternatives from an ideal solution (Aruldoss, Lakshmi, and Venkatesan 2013).

As an example, Aliakbari Nouri, Khalili Esbouei, and Antucheviciene (2015) presented an MCDM-based approach to select a suitable manufacturing technology considering both qualitative and quantitative factors, including human resources, financial considerations, and operational dimensions. In another example, Chan et al. (2006) proposed an MCDM-based decision support system that assists manufacturing process selection in an uncertain environment. This decision support system is designed to reduce conflicts between tangible factors, such as cost and intangible factors, such as quality. More examples of the introduction and application of various MCDM-based methods for manufacturing process selection are presented in the studies by Bikas, Porevopoulos, and Stavropoulos (2021), Ren, Choi, and Schneider (2022), Salmi et al. (2024), Douglas C. Eddy, Krishnamurty, and Steudel (2019), Foshammer et al. (2022), Kadkhoda-Ahmadi, Hassan, and Asadollahi-Yazdi (2019), Polydoras, Vossou, and Koulocheris (2020), and Breaz, Bologa, and Racz (2017). A review of MCDM methods in manufacturing process selection by Hamzeh and Xu (2019) highlights a significant increase in the use of these methods for this purpose.

While MCDM methods address some of the issues of the elimination-based methods such as the consideration of a larger number of factors and a more systematic decision-making process through the use of techniques such as AHP and TOPSIS, the majority of them still presume the existence of a complete design. This is contrary to guidelines such as DfAM, which suggest that to take full advantage, the manufacturing process must be considered in parallel with the design process, starting from the earlier stages.

2.5. Multi-criteria decision support for AM

MCDM-based approaches and methods are also explored specifically for AM applications (Rai et al. 2022). For example, Bertolini, Esposito, and Romagnoli (2020) implemented a TOPSIS-based MCDM approach to select the optimal manufacturing method in the food and beverage industry. While the validation study resulted in effective outcomes, the focus was on the application of this type of method rather than providing guidance on which factors to consider in the comparison process. Similarly, Qin et al. (2020) developed a new MCDM approach that accounts for process performance and user preferences for selecting suitable AM processes. The contribution is unique as it captures user risk attitudes and minimises the negative impact of value distortion. However, similar to Bertolini, Esposito, and Romagnoli (2020), the emphasis is on the method itself rather than on providing guidance on which elements to consider.

A few MCDM studies do offer such guidelines when deciding on the optimal manufacturing process. For instance, Douglas C. Eddy, Krishnamurty, and Steudel (2019) introduced a method that uses technical and economic criteria to compare different manufacturing processes, including AM. However, this method lacks quality assessment considerations; introducing AM as an alternative manufacturing process might require new or adapted quality assurance and control measures. These additional steps may result in additional costs and are often overlooked when making such assessments (Pereira, Kennedy, and Potgieter 2019). Another example is Schuhmann et al. (2022), who proposed a decision support system based on AHP, offering guidelines for product-, process- and production-relevant elements to consider when determining the suitability of AM. However, their method does not address the feasibility of AM, which significantly impacts decision-making. The availability of suitable AM materials and machines, and limitations related to build chamber size are examples of crucial factors that should be included. More examples of MCDM methods for AM process selection can be found in works by Algunaid and Liu (2022), Canciglieri, Sant'Anna, and Machado (2015), Deppe and Koch (2016), Canciglieri, Krüger, and Sant'Anna (2016), Raffaeli et al. (2021), Reiff et al. (2019), Wang, Zhong, and Xu (2018), Borille et al. (2010), Prabhu and Ilangkumaran (2019), Raigar et al. (2020), Ren, Choi, and Schneider (2022), Vinodh, Nagaraj, and Girubha (2014), and Yildiz and Uğur (2018).

One of the main advantages of these methods is their ability to assess the type of manufacturing process early in the design phase before the detailed geometry is defined. An early assessment allows for the application of suitable design for X (DfX) guidelines, optimising the overall process. Another key advantage is the integration of engineers' expertise into the decision-making process. Therefore, a robust MCDM-based decision support system that not only suggests suitable manufacturing processes but also provides clear guidance on which factors to consider when comparing AM with other manufacturing methods is essential.

2.6. Geometry-based decision support for AM

The final type of decision support identified in the literature uses geometry as a criterion for comparing AM with other manufacturing processes. For instance, Ghiasian et al. (2020) proposed a feasibility analysis method for AM that evaluates product geometry using a multi-criteria assessment. This method voxelises a 3D CAD model and assesses it against seven criteria, including dimensions, geometry, build and support orientation, as well as resources for build and post-processing, compared to the specifications of available AM machines. A feasibility score is then assigned based on these criteria. Similarly, Tedia and Williams (2016) presented another voxel-based approach, where manufacturability is analysed using factors such as feature size, negative features, and support material. In another example, the automated tool proposed by Winkler, Stürmer, and Konrad (2021) introduced an index to assess the feasibility of AM based on part geometry and machine constraints, such as build volume. Similarly, Coatanéa et al. (2021) developed a method using dimensional analysis and singular value decomposition to evaluate manufacturability by comparing part designs to an ideal reference for different manufacturing processes. Shi et al. (2018) introduced a feature-based approach using Heat Kernel Signature to recognise geometric constraints affecting manufacturability, automating feature identification for AM feasibility analysis. This category of methods requires CAD files, and, therefore, a pre-existing part design, which limits the ability to fully exploit design-related benefits of AM, as also explained in Section 2.4.

A second set of methods uses artificial intelligence (AI) to assist in selecting the optimal manufacturing process. Ördek and Borgianni (2023) applied unsupervised learning to classify CAD models of different parts, determining whether AM or conventional manufacturing (CM) is the appropriate manufacturing process. Their method focuses solely on product geometry for classification, without considering other influential factors such as product criteria and process constraints. Page, Yang, and Zhao (2019) and Yang et al. (2020) introduced a supervised machine learning (ML)-based decision support framework, incorporating not only part geometry analysis but also process constraints and AM value-added characteristics. However, their approach does not adequately account for product-specific requirements, which are critical for a comprehensive manufacturability assessment.

Further, Ying Zhang and Zhao (2022) developed a printability prediction model that integrates geometric data, material and process information using a convolutional neural network. This approach helps users, particularly novices, evaluate the feasibility of AM and optimise designs to improve print outcomes. Similarly, Ying Zhang (2022) extended this concept by implementing a hybrid ML-based manufacturability assessment system that voxelises 3D CAD models and incorporates process-specific parameters to generate a printability map, highlighting manufacturability issues and suggesting design modifications. These methods and similar commercial tools such as PrintSyst.ai (2025) focus primarily on AM feasibility rather than evaluating its suitability in comparison to other manufacturing methods, which limits their usefulness in broader process selection scenarios.

Both sets of methods (i.e. mathematical and AI-based) are applicable only in cases where parts already exist, meaning manufacturing decisions are made post-facto, which limits the potential for realising the design-related advantages of AM.

2.7. Critique of the state of the art

To summarise, the discussion on available types of decision support in the selection of manufacturing processes, especially considering AM, highlights the following gaps. First, manufacturing process selection methods based on elimination primarily focus on the feasibility of material and manufacturing process combinations and do not consider suitability aspects, which are equally important to investigate. Further, they consider only a few factors in the decision-making, which may not give a realistic assessment of the alternatives. In contrast, some MCDM approaches, which do enable decision-making in the early phases of design, however often lack systematic guidance on which factors to consider in the comparison or to what extent. This limits their ability to leverage potential benefits of different DfM and DfAM guidelines, as early selection of a manufacturing method allows for design optimisation based on the unique capabilities of various manufacturing methods.

Second, methods that use geometry to assess the feasibility of AM compared with other manufacturing processes require detailed product geometry. Such assessment deals with a low level of uncertainty as most design decisions are already made, however, it might lead to suboptimal results if the product was not originally designed for the most suitable manufacturing process, such as AM. On the other hand, methods based on MCDM are applicable earlier in the design phase before the detailed design is finalised, which introduces more uncertainty. However, these methods are beneficial as deciding early on the manufacturing process can influence and tailor the design process. Despite their benefits, many existing MCDM methods lack a comprehensive framework for identifying the critical factors that need to be considered when making these decisions.

Overall, both product- and process-related information must be accounted for in these assessments. Further, clear guidelines to select the manufacturing process must be provided before the design process commences, so that the opportunity to consider the potential advantages offered by AM remains as the design progresses. This is a clear gap in the literature which needs to be addressed. In the next section, we explore the key factors which influence decision-making in the pre-conceptual design phase. In this paper, the term pre-conceptual design refers to the point in the design process before the organ structure exists (e.g. in the procedural model of Hubka and Eder 1996).

3. Key influencing factors

To gain the most out of AM, the decision to use AM or not should be made even before the design commences. The decision depends on a few key influencing factors, which can help in determining the suitability of AM as a manufacturing method. In this section, we present a list of such factors, synthesised from literature and a previous empirical study conducted by the authors on three large-scale Swedish companies (Hajali et al. 2023; Isaksson et al. 2024). These factors include both product and process-related considerations which are elaborated below.

3.1. Product-related factors

Primary and secondary functions. In most design process models, the elicitation of functions from requirements generally precedes the emergence of structure (Wynn and Clarkson 2018). While structure enables the fulfilment of these functions, it also constrains the manufacturing process by determining the physical form the product will take. Logically, any decisions regarding the manufacturing process should be considered at the point where the functions are converted to the structure. In the context of AM, researchers point to the lack of consideration of functions as a factor in manufacturing process selection (Douglas C. Eddy, Krishnamurty, and Steudel 2019; Hedberg Jr et al. 2017). For instance, methods that consider only geometry (Section 2.6) to determine process suitability largely ignore product function (Molina et al. 2022). In contrast, in MCDM approaches the definition of criteria is somewhat flexible, which allows some methods to use functionality indirectly and some to ignore it completely. For instance, the decision support method proposed by Eddy et al. (2016) starts with investigating product critical functions followed by requirements analysis. This creates a basis for generating design concepts, followed by selecting a suitable manufacturing process alternative. In another example, the manufacturing evaluation framework suggested by Garzaniti, Golkar, and Maggiore (2019) uses the primary functionality of the product in defining the design space. Function analysis in the pre-conceptual design phase can not only increase the novelty of ideas by better exploration of the design space (Fu et al. 2014), it can ensure better utilisation of manufacturing capabilities, for example through DfX methods, once the method is chosen.

Design criteria and requirements. A design must meet certain criteria and requirements, both functional and non-functional (Pahl et al. 1996; Ulrich, Eppinger, and Yang 2019), which can significantly influence the manufacturing process (Vallhagen et al. 2013). While functional requirements influence embodiment, which in turn influences the manufacturing process, non-functional requirements such as those related to product life, quality, and maintenance can also have a strong impact on the manufacturing method (Agrawal and Vinodh 2019). As a result, the type and configuration of the manufacturing process need to be carefully determined before a manufacturing decision is made (Deppe, Lindemann, and Koch 2015).

As an example, Bertolini, Esposito, and Romagnoli (2020) incorporated criteria such as desired surface roughness, weight, and dimensional constraints when comparing different manufacturing processes using TOPSIS MCDM-based approach. In another example, Klahn et al. (2020) considered required quality aspects such as product critical mechanical properties into account when evaluating AM for remanufacturing a product for better value creation. Required material properties, part accuracy, robustness and minimum feature size are some other examples (see Bikas, Koutsoukos, and Stavropoulos 2019; Canciglieri, Krüger, and Sant'Anna 2016; Meisel et al. 2016; Raffaeli et al. 2021; Wang, Zhong, and Xu 2018; Williams, Mistree, and Rosen 2005; Zheng et al. 2017).

Value added characteristics. The choice of manufacturing method also depends on the value that different methods can add. For instance, AM offers greater design freedom, the potential for lighter designs, internal channels and structures, part consolidation leading to function integration, and the possibility of different surface and material structures (Diegel, Nordin, and Motte 2019; Yang et al. 2020). These added characteristics should therefore be considered when analysing the suitability of AM for a given product design. The importance of considering added value for manufacturing processes also lies in reducing the cognitive biases (Reichwein et al. 2021; Seepersad 2014) regarding the process constraints, which engineers may have developed due to years of experience in using traditional manufacturing methods (Thompson et al. 2016). Westerweel, Basten, and van Houtum (2018) for instance, defined a metric that serves as a proxy for performance gained from incorporating unique design elements only possible using AM in their proposed model. They further use this metric in a broader calculation to compare the influence of different manufacturing scenarios based on product lifecycle cost. In another example, Kruse, Reiher, and Koch (2017) incorporated a criterion to reflect lightweight and functional integration potential to decide on the suitability of AM. Yang et al. (2020) considered aspects such as the possibility of internal channels, surface markings and human body compliance to identify products suitable to be manufactured with AM.

3.2. Process-related factors

Resource availability. The availability of AM material, equipment and machines directly affects the feasibility of the AM process (Reiff et al. 2019; Wang, Zhong, and Xu 2018). For instance, in the decision support proposed by Achillas et al. (2015), besides determining the important product criteria such as thermo-mechanical requirements, the availability of different technologies and infrastructure is used to create a list of available options. These options serve as inputs to a decision support tool that takes into account expert opinion and company strategy to propose an optimal production strategy. The framework proposed by Foshammer et al. (2022) includes a phase zero stage in manufacturing process decision-making where the feasibility of AM is investigated. Among many factors, the availability of equipment, as well as the design and operator capabilities related to AM, are assessed, as these directly influence the suitability of AM for manufacturing a product.

Resource characteristics. The type and properties of AM machines and materials require careful consideration, as they have a significant effect on the characteristics of the produced artefact (Ashby 2005). For example, the material resources available would have a direct effect on the mechanical properties of the material. Additionally, the energy source of an AM machine may influence the manufacturing outcome in terms of microstructure and consequently quality requirements (Malakizadi et al. 2021). Willmann (2019), for instance, implemented a material database consisting of modified Ashby charts and a production techniques repository as a means to facilitate economic analysis of AM application. Material and machine databases, for instance, can be useful for this purpose and are implemented by methods proposed by Kadkhoda-Ahmadi, Hassan, and Asadollahi-Yazdi (2019), Reiff et al. (2019), Liu, Zhu, and Ye (2020), Ren, Choi, and Schneider (2022), and Uz Zaman et al. (2018).

Resource constraints. While closely related to resource characteristics, resource constraints limit the extent to which certain artefact characteristics can be achieved. Examples include constraints on build volume dimensions, compatibility of different AM machines and materials, printing speed and dimensional accuracy (Liu, Zhu, and Ye 2020; Prabhu and Ilangkumaran 2019; Qin et al. 2020; Ren, Choi, and Schneider 2022; Yildiz and Uğur 2018). Additionally, constraints such as lead time and cost must also be taken into account. Costs associated with sourcing, design, manufacturing, assembly, labour and delivery must be accounted for to decide whether AM can be used or not (Douglas C. Eddy, Krishnamurty, and Steudel 2019; Schuhmann et al. 2022). As an example, Garzaniti, Golkar, and Maggiore (2019) provided a cost breakdown for the AM process, from build preparation to the quality assessment phase, as one of the important elements to assess the suitability of AM. In another example, Ghiasian et al. (2020) presented a method to estimate the time and cost of AM as one of the critical factors to determine the suitability of AM as one of the critical factors in determining its suitability for manufacturing a product.

Batch size. The number of parts to be produced affects not only the lead time and cost, but also resource consumption. Hopkinson and Dicknes (2003), for instance, showed the critical impact of production volume on manufacturing cost, highlighting significant differences between AM processes and traditional methods. Eddy et al. (2016) considered product quantity as one of the main drivers in determining whether AM is an economic alternative compared to other manufacturing processes. Further, they incorporated this factor in their decision support to demonstrate its influence on product cost. Other decision-support examples that incorporate batch size as a factor include Willmann (2019) and Achillas et al. (2015).

Quality assurance and control. The choice of the manufacturing process also has significant implications on quality assurance and control of the product (Pereira, Kennedy, and Potgieter 2019). In cases where AM is introduced in the portfolio of existing conventional processes, quality assurance procedures may need to be reassessed, resulting in additional process steps and costs. An industrial case study detailed in (Hajali et al. 2024) highlights the importance of both quality assurance and quality control considerations when making such decisions. Schuhmann et al. (2022) considered quality management factors such as process repeatability in comparing AM with other manufacturing processes. However, their methodology applies to geometry analysis rather than suitability assessment in the pre-conceptual design assessment. The manufacturing cost analysis by Garzaniti, Golkar, and Maggiore (2019) includes quality control phase elements such as costs related to validation and documentation, however, it does not explicitly address the additional costs and time dedicated to re-evaluating the quality assurance procedures.

3.3. Sustainability-related factors

An important consideration in making informed manufacturing process decisions is its impact on sustainability. Sustainability extends beyond environmental aspects, encompassing a balanced integration of three interconnected aspects: people, profit, and planet, which continuously influence one another (Geissdoerfer et al. 2017). A number of studies have proposed decision support frameworks to assess the environmental impact of AM compared to CM. For instance, Vimal et al. (2016) and Chandra et al. (2022) developed MCDM-based models that compare AM processes based on criteria such as energy efficiency, material waste, and process emissions. Similarly, Yosofi, Kerbrat, and Mognol (2018) proposed a framework integrating technical, economic, and environmental factors, including energy and material consumption, to guide AM process selection. Additionally, Watson and Taminger (2019) analysed energy consumption differences between AM and subtractive manufacturing, highlighting process efficiency considerations.

Beyond these specific models, broader comparative studies have been conducted. Santos et al. (2012) applied life cycle assessment (LCA) to quantify the environmental impacts of AM across different life cycle stages, while Paris et al. (2016) proposed a framework for assessing AM and CM based on ten environmental indicators, including global warming potential, acidification, and water consumption. Wenjin Zhang, Zhang, and Zhang (2020) further contributed by proposing a decision support model that evaluates material efficiency and consumption across the life cycle. Schuhmann et al. (2022) and Polydoras, Vossou, and Koulocheris (2020) extended these considerations by incorporating sustainability factors such as resource efficiency, recyclability, and the impact of auxiliary equipment into decision-making systems.

In addition to the environmental aspect, economic and social dimensions of sustainability need to be integrated into the decision-making process. While several studies have considered economic sustainability, including lifecycle cost analysis comparing AM with other manufacturing processes (e.g. Peron et al. 2024; Westerweel, Basten, and van Houtum 2018), the social influence of AM is largely overlooked (Naghshineh et al. 2021). To achieve a comprehensive analysis, all three sustainability aspects must be considered.

Table 1. Key influencing factors affecting suitability analysis of AM.

Domain	Factors	Examples
Product	Primary and secondary functions	Lift an object, transfer fluid
	Design criteria/requirements	Surface roughness, heat resistance, load durability
	Value added characteristics	Customization, lightweight design, possibility of internal channels, functional integration, different surface and material structure
Process	Resources availability	Availability of different AM machines and materials
	Resource characteristics	Material properties such as yield strength or conductivity, AM machine properties such as type of energy source or printing speed
	Resource constraints	Lead time and cost constraints, internal or external access to the AM machines, compatibility of different AM machines and materials
	Batch size	Per order, annual
	Quality assurance control	If AM is applicable, do new quality assurance procedures need to be defined? How can the quality be assessed? How can the repeatability of the result be assured? What would be the effect of these considerations on lead time and cost?
Sustainability	Both regarding the product and process	Economic aspect (resource consumption), environmental aspect (such as energy consumption), and social aspect (such as the impact on engineers and end users)

This can be challenging, especially in the pre-conceptual design phase when information about the product and process is limited. The complexity of such an assessment is further highlighted by Hajali et al. (2024) and Despeisse, Hajali, and Hryha (2024).

3.4. Summary

To summarise, seven key factors are identified that must be considered when deciding whether or not AM should be used, particularly in scenarios where the assessment is not straightforward. These factors are summarised in Table 1, categorised under three domains of Product, Process and Sustainability, which answers RQ1. Further, Table 2 summarises the factors addressed by the relevant methods in the literature.

Based on the identified gaps in the literature, discussed in Section 1 and the key factors that need to be considered in this section, a method is presented in the next section. This method integrates these factors to provide decision support for designers and managers in the pre-conceptual design phase of a product, thereby addressing RQ2.

4. MPDS method and tool

With the introduction of AM, many of the constraints associated with traditional manufacturing have been eliminated. However, they have been replaced with new ones, which creates new challenges for designers as they must adjust to a fundamentally different set of limitations. To fully benefit from the potential of AM (Borgue et al. 2019; Diegel, Nordin, and Motte 2019), the constraints associated with AM must be considered explicitly. The factors outlined in Section 2 represent key considerations that support this assessment, but to be practically useful, they need to be arranged in a logical sequence to provide meaningful support. Therefore, in this section, we introduce a method which organises the key influencing factors in a logical structure to help designers make informed decision about whether

Table 2. Identified key factors addressed in relevant literature.

	Product			Process					Sustainability
Papers/Factors	Primary & Secondary Functions	Design criteria & Requirements	Value added characteristics	Resources availability	Resource characteristics	Resource constraints	Production volume	QA & QC	Social or Environmental
Achillas et al. (2015)		✓		✓	✓	✓	✓		
Bertolini, Esposito, and Romagnoli (2020)		✓			✓	✓	✓		
Bikas, Koutsoukos, and Stavropoulos (2019)		✓	✓			✓	✓		✓
Douglas C. Eddy, Krishnamurty, and Steudel (2019)	✓	✓	✓		✓	✓	✓		
Foshammer et al. (2022)				✓		✓	✓		
Garzaniti, Golkar, and Maggiore (2019)	✓	✓	✓			✓	✓	✓	
Ghiasian et al. (2020)					✓	✓			
Hopkinson and Dicknes (2003)		✓			✓	✓	✓		
Kaspar et al. (2018)		✓	✓			✓			✓
Klahn et al. (2020)			✓	✓		✓	✓		
Kruse, Reiher, and Koch (2017)		✓	✓		✓	✓			
Yang et al. (2020)			✓		✓	✓	✓		✓
Peron et al. (2024)			✓	✓		✓			
Schuhmann et al. (2022)			✓			✓	✓	✓	✓
Watson and Taminger (2019)					✓				✓
Westerweel, Basten, and van Houtum (2018)			✓			✓			
Willmann (2019)	✓	✓	✓		✓	✓	✓		
Wenjin Zhang, Zhang, and Zhang (2020)									✓
Sgarbossa et al. (2021)		✓	✓		✓	✓	✓		
Achillas, Tzetzis, and Raimondo (2017)					✓	✓	✓		
Yosofi, Kerbrat, and Mognol (2018)		✓			✓	✓			✓
Santos et al. (2012)									✓
Paris et al. (2016)									✓
Polydoras, Vossou, and Koulocheris (2020)		✓		✓		✓			✓

(*continued*).

Table 2. Continued.

	Product			Process					Sustainability
Papers/Factors	Primary & Secondary Functions	Design criteria & Requirements	Value added characteristics	Resources availability	Resource characteristics	Resource constraints	Production volume	QA & QC	Social or Environmental
Bikas, Koutsoukos, and Stavropoulos (2019)		✓	✓	✓		✓	✓		
Canciglieri, Krüger, and Sant'Anna (2016)		✓				✓			✓
Raffaeli et al. (2021)		✓	✓	✓	✓	✓	✓		
Wang, Zhong, and Xu (2018)		✓		✓		✓			
Williams, Mistree, and Rosen (2005)		✓			✓	✓		✓	✓
Zheng et al. (2017)	✓	✓			✓	✓	✓		
Reiff et al. (2019)		✓		✓	✓				✓
Prabhu and Ilangkumaran (2019)		✓			✓	✓			
Qin et al. (2020)		✓			✓	✓			
Kadkhoda-Ahmadi, Hassan, and Asadollahi-Yazdi (2019)		✓			✓	✓			
Liu, Zhu, and Ye (2020)		✓			✓	✓	✓		
Ren, Choi, and Schneider (2022)		✓			✓	✓			
Uz Zaman et al. (2018)	✓	✓			✓	✓			✓
Yildiz and Uğur (2018)					✓				
Vimal et al. (2016)		✓			✓	✓			✓
Chandra et al. (2022)		✓	✓	✓	✓	✓	✓		✓

or not to consider AM as a manufacturing option. A tool which implements the method is then presented.

4.1. MPDS method structure

The MPDS method consists of two main components:

(1) ***Feasibility analysis:*** Feasibility analysis checks for violations of production and design criteria and requirements against known resource constraints, characteristics, and availability. Factors such as the availability of AM machines and materials, as well as build volume limitations, determine whether AM can be used.
(2) ***Suitability analysis:*** Suitability, in contrast, focuses on the appropriateness of AM as a manufacturing choice, given the context of the product and the process. The context is defined by considerations such as batch size and design characteristics, such as lightweight structures. Suitability provides an indicator of whether any benefits can be gained by using AM over other manufacturing methods by systematically comparing AM with them for a specific product.

Figure 1 provides a high-level overview of the MPDS method. The key factors outlined in Section 2 are incorporated as inputs, ensuring that the method captures essential elements for conducting such a comparison. Sustainability-related factors are deliberately excluded, as further research in collaboration with sustainability experts is required.

The MPDS method begins with the feasibility analysis of AM, assessing whether AM is viable within the current configuration. If infeasible, input parameters can be adjusted (if possible) to enhance feasibility before proceeding further. Once feasibility is established, the suitability of AM is evaluated by comparing it with conventional manufacturing. As product development progresses in the pre-conceptual design phase, new information becomes available, allowing for an iterative reassessment of both the feasibility and suitability of AM. This iterative approach ensures that if AM remains a viable option throughout the design process, necessary adjustments can be made based on insights gained from the feasibility and suitability assessments, maximising its full potential, including in the ideation stage.

4.2. Feasibility analysis of AM

Figure 2 demonstrates the flowchart used for analysing the feasibility of AM in MPDS. Both process-related and product-related factors are considered. The process follows a step-by-step screening of infeasible options. Initially, a list of available AM machines is compared against the estimated product dimensions. Machines with build volumes smaller than the required size are excluded. Next, the remaining machines are assessed for compatibility with the available AM materials. As mentioned earlier, machine-material compatibility is analysed, resulting in a refined list of compatible AM machines and materials. In the final screening phase, the product's necessary criteria and requirements are compared against the properties of the feasible materials, as indicated in the material data sheets. Certain materials may meet specific criteria or requirements, further narrowing down the list of feasible materials and machines. As a result, a final list of available and feasible AM machines

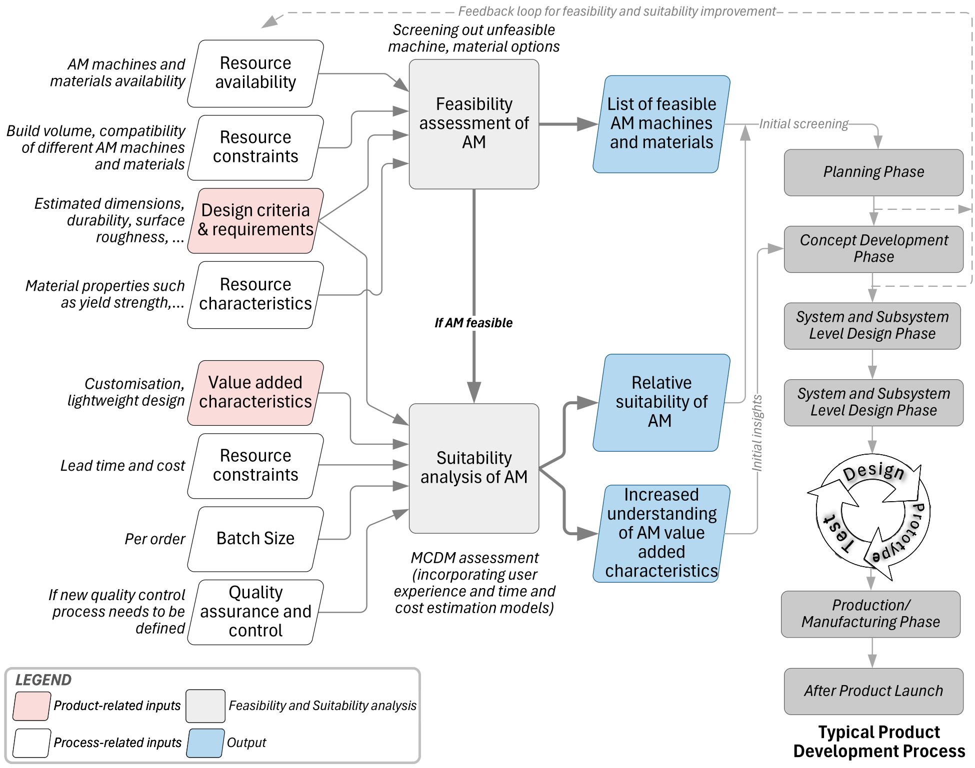

Figure 1. Overview of MCDM structure and its position in a typical product development process.

and materials is compiled. If the list is empty, AM is considered infeasible under the defined conditions.

4.3. *Suitability analysis of AM*

Once feasibility is established, the next step is to evaluate the suitability of the remaining AM processes within the application context. As shown in Figure 1, the key factors necessary for suitability evaluation include product-related inputs such as design criteria and requirements, and the AM value adding characteristics. It also requires input from process-related considerations such as resource constraints (e.g. lead time, cost and batch size, as well as aspects of quality assurance and control). These elements are used as inputs for two main analyses explained in Sections 4.3.1 and 4.3.2 serving as inputs to the MCDM analysis explained in Section 4.3.3. These sections are highlighted in pink in Figure 3. For simplicity of demonstration, the focus is on comparing one AM process against one relevant traditional method. However, in practice, the inclusion of multiple methods in the analysis is possible.

4.3.1. *Comparison of product critical criteria and requirements with AM value-enabling characteristics*

Drawing from the list of factors discussed in Section 3.1, the functional and non-functional criteria and requirements that a product must meet significantly influence the choice of the

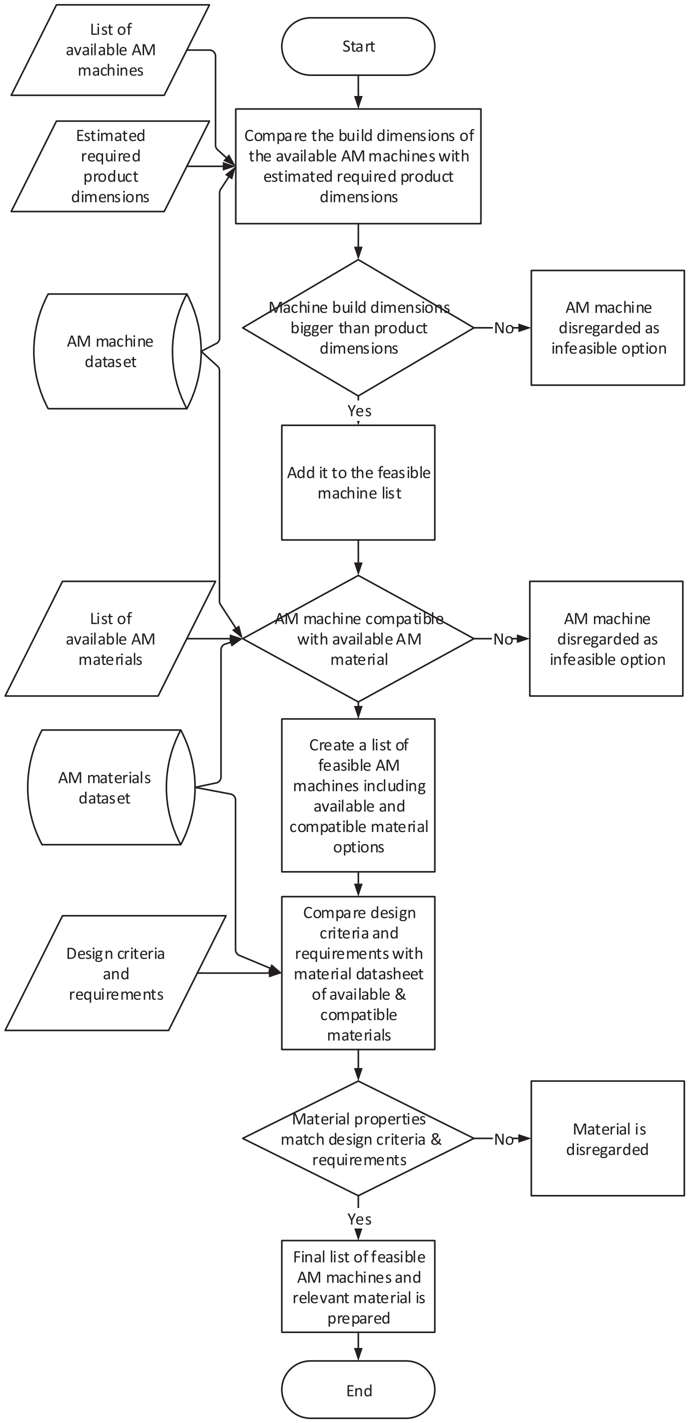

Figure 2. Overview of MCDM feasibility analysis of AM.

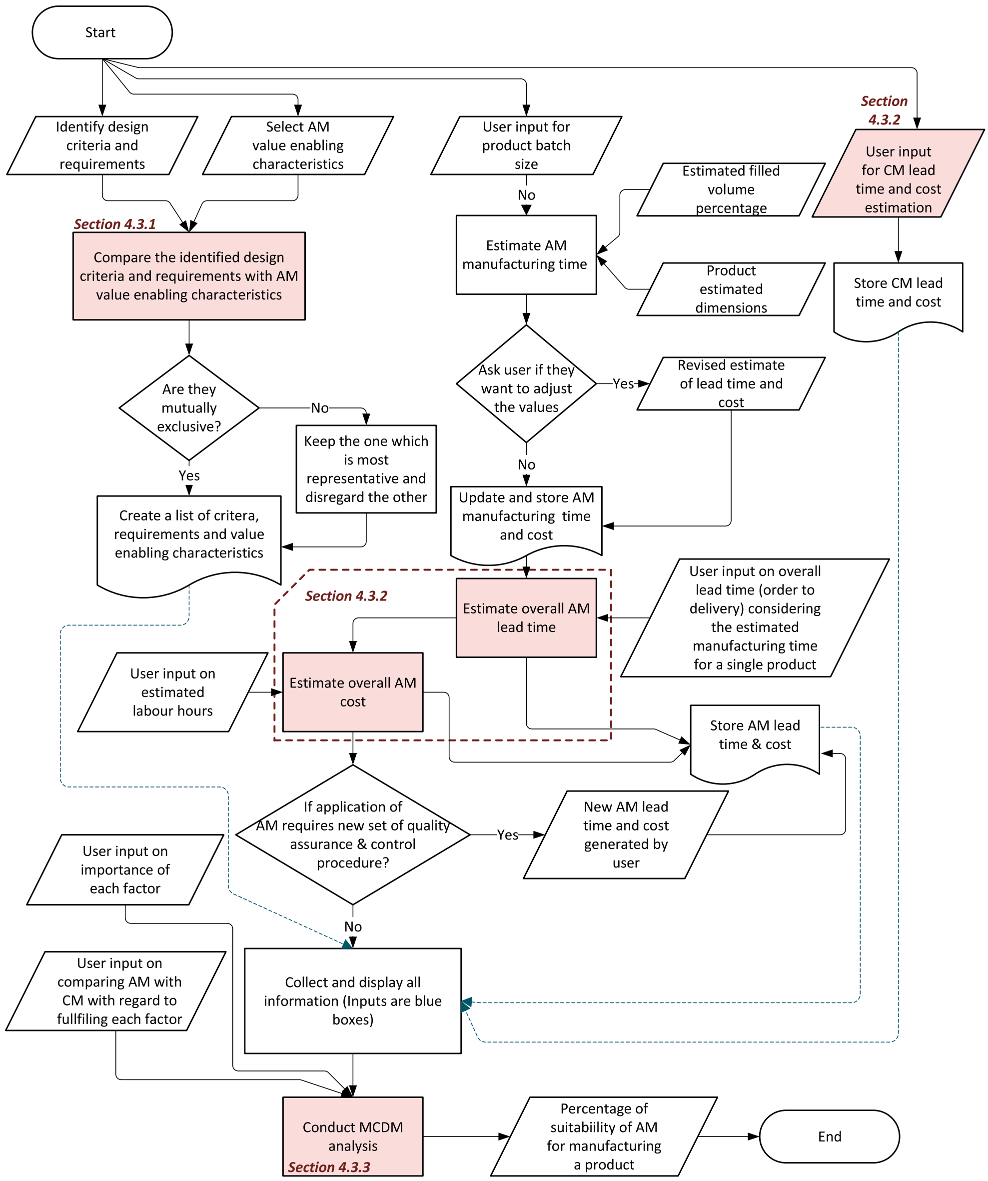

Figure 3. Flowchart showing the suitability analysis of AM according to the MCDM method. Dashed lines indicate inputs to the MCDM analysis. Material and machine information are included in the analysis but removed from the figure for simplicity.

manufacturing process. Therefore, the first step in analysing suitability is to elicit the relevant product criteria and requirements in a list. Requirements related to, for instance, load durability and surface roughness, are included without consideration of potential manufacturing process limitations. In parallel, a list of relevant value-enabling characteristics of AM is prepared, which may include characteristics such as customisation, the possibility of internal channels/structures, lightweight design, functional integration, different material options and surface structures.

The two lists are then compared to eliminate redundancies. For example, if an ergonomic structure is one of the criteria, it may share similarities with the lightweight design enabled by AM. If both refer to the same criterion, one is removed. Alternatively, if the items represent distinct requirements, they are clarified to be more specific such that they can be differentiated explicitly. The final output is a list of characteristics which is then used as input for the MCDM analysis discussed in Section 4.3.3.

4.3.2. Estimation of lead time and cost

The second input for the MCDM process is the estimation of lead time and cost. The assessment method presented in this section considers not only the manufacturing phase but also the entire production cycle, including design, pre-processing, manufacturing, post-processing, quality control and delivery. As limited data are available in the pre-conceptual design phase regarding the product and the process, the estimation method relies on information such as whether AM machines are available in-house or whether production is outsourced, which significantly affects the lead time and cost. Additionally, previous experience with similar products can also be used to inform the estimate. In the MPDS methodology, the alternative suitable conventional manufacturing method and associated average lead time and cost parameters are derived from expert opinion. For estimating the lead time and cost of AM, however, the following methodology is applied to elicit an estimate of both.

Estimation of lead time for the AM process

An approximate time estimate can be made based on the estimated product dimensions and a typical printer setup:

l = *Required length of the part*
h = *Required height of the part*
d = *Required depth of the part*

Several studies have proposed methods for estimating the manufacturing time of different AM processes, including Baumers et al. (2012), Yim and Rosen (2012), Yicha Zhang and Bernard (2013), Amini (2014), Baumers et al. (2015), Yicha Zhang et al. (2015), Komineas et al. (2018), and Machado et al. (2020). In this paper, a simplified model is presented assuming material extrusion as the AM process; however, the method can be adapted to other AM processes by incorporating the approaches discussed in the referenced articles. This leads to the following AM manufacturing time estimation equation, referred to as (T_1):

$$T_1 = T_r \times R_l \times L_n \times V_f \tag{1}$$

Where T_r is the time to print a row, R_l is the number of rows per layer, L_n is the number of layers, and V_f is the estimated filled volume percentage. Further,

$$T_r = \frac{l}{s} \tag{2}$$

where, s is printing speed.

$$R_l = \frac{d}{w} \tag{3}$$

where, w is layer width.

$$L_n = \frac{h}{L_h} \tag{4}$$

where, L_h is the layer height (considering 75% of the nozzle size Fischer et al. 2022).

The exact shape of the product directly influences the printing time, which is, however, difficult to determine in the pre-conceptual design phase. Since the product is unlikely to be a simple cube, the movement of the nozzle will be more complex than initially assumed. On one hand, the product may require less material, potentially reducing the printing time. On the other hand, increased geometric complexity can lead to longer printing times. These factors impact the printing time in contrasting ways and are highly case-dependent. As the goal is to provide a rough estimate, the calculation is kept simple by assuming these factors have a negligible effect.

In scenarios where more than one product is ordered, the batch size (N) influences the lead time of AM. Assuming the products are printed individually, the overall printing time is calculated as:

$$T_n = T_1 \times N \tag{5}$$

The remaining processes, including design, pre- and post-processing, quality assessment, and delivery, do not necessarily have a direct correlation with batch size. For example, while the design phase remains unaffected by the batch size, post-processing may need to be repeated multiple times. Aside from the printing time, phases exogenous to the printing, such as design (T_1), pre-processing (T_{pre}), post-processing (T_{post}), quality control (T_{qc}), and logistics (T_{log}) add to give the total lead time for one part.

$$T_{lead} = T_1 + T_{des} + T_{pre} + T_{post} + T_{qc} + T_{log} \tag{6}$$

The factors considered in Equation 6 are highly dependent on a specific product and a company's circumstances. For instance, whether the product needs to be delivered externally or used in-house will directly affect the lead time. Therefore, the engineer should first estimate the manufacturing time using the guideline above, and based on that, account for additional phases in the value chain to estimate the lead time for a single product if manufactured by the specified AM process. Any other exogenous factors not included in Equation 6, must therefore be added based on a company's value chain design.

To provide a rough estimate of lead time for a batch size of N, it is assumed that half of the total process scales with the batch size, while the other half remains constant:

$$T_{total} = T_n + \tfrac{T_{lead} - T_1}{2} \times (1 + N) \tag{7}$$

Although T_{total} estimated here is a rough approximation and may not be accurate, it still offers engineers an initial idea of which elements to consider in the calculation. For better estimation, engineers can determine the total lead time based on specific process factors.

Estimation of cost for the AM process

Similar to the lead time estimation, there are a number of cost estimation models available in the literature. Drawing from Thomas and Gilbert (2014), Costabile et al. (2017), and Groover (2010), the total cost for a batch of prints is estimated by summing costs related to material (C_{mat}), labour (C_{lab}), the machine (C_{mch}) and overhead (C_{over}).

$$C_{total} = C_{mat} + C_{lab} + C_{mch} + C_{over} \tag{8}$$

10% of the overall cost is considered as the estimated value for the overhead cost (C_{over}) according to Atzeni and Salmi (2012). The material cost C_{mat} can further be calculated using the material weight (M_w) and the material price per unit weight (C_w). For a batch size of N:

$$C_{mat} = M_w \times C_w \times N \tag{9}$$

where, M_w is calculated based on the material density (M_d), the volume, and the fill density V_f:

$$M_w = M_d \times l \times h \times d \times V_f \tag{10}$$

If the user does not define V_f, a default value (e.g. 25%) can be used. Similarly, density (M_d) and cost per gram (C_w) can be considered as the average value for available material.

Further, (C_{lab}) is calculated using the labour time spent on the entire process (T_{lab}) which is estimated by the user, and the hourly labour cost (C_{Tlab}).

$$C_{lab} = T_{lab} \times C_{Tlab} \tag{11}$$

Lastly, AM machine cost ($C_{machine}$) is calculated by multiplying the machine power (P_{mch}), the overall printing time (T_n, Equation (5)), and the electricity rate in cost/kWh (E_r) (Costabile et al. 2017):

$$C_{machine} = T_n \times P_{mch} \times E_r \tag{12}$$

Here an assumption is made that the products are not printed simultaneously in the same chamber, therefore (T_n) instead of (T_1) is used. If products are manufactured in batches, a lower value can be used accordingly.

Influence of quality assurance and control on resource consumption

As explained earlier in Section 2, if AM is introduced as a new technology and the company traditionally manufactures similar products using other processes, the design and material for AM may differ. This necessitates the definition of new quality assurance and control procedures, which directly impact resource consumption. Therefore, after estimating the overall lead time and cost for the AM process, the designer should reassess these values with this in mind. If the lead time or cost is expected to change, the user can manually adjust the values accordingly.

4.3.3. MCDM analysis

Once the list of key criteria, requirements, and AM value-enabling characteristics has been identified, along with lead time and cost estimations for both AM and CM, data is used as input for the MCDM analysis. In this analysis, AM and CM processes are compared. The flow is illustrated in Figure 3.

First, the importance of the various factors–including criteria, requirements, value-enabling characteristics, lead time, and cost–is assessed based on expert opinion, using a scale from 1 to 10, where 1 represents the lowest importance and 10 is the highest. Next, AM and CM are evaluated against these factors. For example, when assessing load durability, if in CM a conventional metal material for a similar product is used, it would receive a higher score compared to a polymer material used in AM. Scores are again assigned on a scale from 1 to 10, based on how well each manufacturing process (AM or CM) satisfies the given factor. These two sets of values–factor weights and comparison scores–are then used to perform the MCDM analysis. Among the widely used MCDM methods, a modified version of the weighted sum model was selected due to its simplicity and its ability to facilitate a well-structured comparison among alternatives (Singh and Malik 2014) (see Equation (13)).

$$M_i = \sum_{j=1}^{n} w_j x_{ij}, \quad \text{for } i = 1, 2, \ldots, m \tag{13}$$

where:

M = Total score of each manufacturing process (AM & CM)

i = Number of alternatives (two, as comparing AM & CM)

j = Number of factors

w_j = Weight of factor f_j

x_{ij} = Score of the manufacturing process (M_i) with respect to f_j

The result of the analysis provides a percentage comparison of the suitability of AM and CM relative to the ideal manufacturing process (M_{ideal}), which receives a maximum score of 10 for each factor (see Equation (14)).

$$\%\text{Suitability of AM} = \frac{M_{AM}}{M_{ideal}} \times 100 \tag{14}$$

5. Example application of MPDS

To demonstrate the application of MPDS in an industrial setting, a prototype computer application implementing the approach was developed (Figure 4). Furthermore, a real industrial case of a lifting tool was taken as an example. The lifting tool was required to assist in lifting of a 3 kg housing (shown in Figure 5) on a production line. The housing shown in Figure 5 has been modified to preserve confidential proprietary information and is therefore represented as an approximation of the actual case. The modification however does not change the application of MPDS and its outcome in any significant way.

Following the MPDS methodology, the key influencing factors affecting the feasibility and suitability assessments of AM are first identified, as presented in Section 5.1. This information is then used to analyse the feasibility of AM. The analysis is presented in Section 5.2, followed by the assessment of the suitability of AM for the specified example, presented in Section 5.3.

5.1. *Identifying key influencing factors*

Using Table 1 as a guide, the key influencing factors affecting the feasibility and suitability of AM for the design and manufacture of the lifting tool are identified and summarised in Table 3. From a product perspective, the tool must be durable to withstand the load and have a long operational life. It needs to enable safe handling of the housing. The design must allow for a stable movement of the housing without any wobble during the lifting process to ensure control and safety. It also needs to have an ergonomic design to accommodate frequent use. Furthermore, it should not damage the surface of the housing during

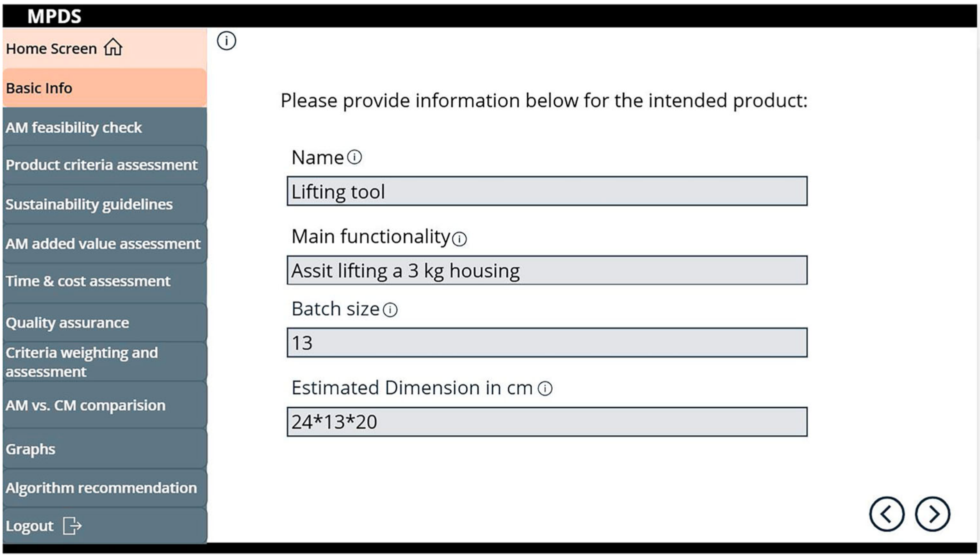

Figure 4. The basic info input screen for the MPDS prototype interface.

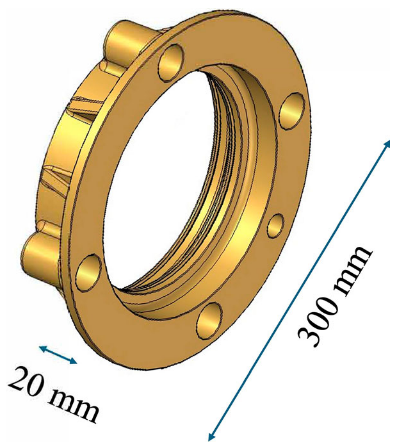

Figure 5. Overview of the housing which the tool needs to facilitate its vertical lift. Figure adapted with permission from Hajali et al. (2024).

transport. Including a design feature that indicates when the tool needs to be replaced (e.g. similar to wear grooves in tyres) would be useful. The tool dimensions should fall within a volume of 240 × 130 × 20 mm^3.

Among the value-enabling characteristics of AM, the potential for customisation and lightweight design was found to be relevant. In addition, the possibility of functional integration can lower the number of parts, so fewer assembly steps are needed.

From a process perspective, two material extrusion printers, Ultimaker S7 and Prusa i3 MK3S, are considered available, with their specifications provided in Table 4. These printers support the materials considered available in this example, including PLA, PETG, ABS and ASA. The required batch size for the product is 13, with a desired lead time to delivery of

Table 3. Key influencing factors affecting feasibility and suitability of AM for the lifting tool.

Domain	Factors	Lifting tool information
Product	Primary	Lift the housing in production line safely
	Design criteria/requirements	Enable lifting of 3 kg housing, load durable, avoid wobbling during lifting, Enable a safe lifting process, have an ergonomic design, design enable warning for when to replace the tool, does not damage the surface of the housing during lifting. The dimensions of the product should be within the range of $240 \times 130 \times 20\,\text{mm}^3$
	Value added characteristics	Customisation, lightweight design, functional integration
Process	Resources availability	Available printers: Printer A, Printer B, Available material: PLA, PETG, ABS and ASA in two different filament sizes
	Resource characteristics	AM machines and material data sheets are available
	Resource constraints	Should be delivered within two months and cost less than 2000 SEK per unit. Printers constraints including printing dimensions and compatible materials need to be considered (see Table 4).
	Batch size	13
	Quality assurance control	This product has a direct connection with the safety of the operators, therefore quality assurance and control are critical. Currently, a procedure for quality assurance and control for similar products manufactured by CM exists and can be reused for this product. In the case of using AM, a deeper investigation of quality assurance and control is needed.

Table 4. Available printers specifications.

Name	Main Compatible Material	Printing Dimensions (mm^3)	Approximate High-Quality Speed (mm/s)	Nozzle Size (mm)	Power (W)
Ultimaker S7	PLA, PVA, PETG, ABS, PC, CPE, Nylon, PP, TPU	$330 \times 240 \times 30$	20–40	0.4	500
Prusa i3 MK3S	PLA, PETG, ASA, ABS, PC, CPE, PVA, TPU, PP, Nylon	$250 \times 210 \times 210$	30–50	0.4	120
Average			35	0.4	310

two months and a maximum unit cost of 2000 SEK. Conventional manufacturing of similar products typically involves casting and machining, which includes established quality assurance and control procedures in the factory setting. Transitioning to AM requires additional investigations and effort into the quality assessment procedures, which may increase delivery time and resource consumption.

5.2. *Feasibility analysis of AM*

Following the approach in Figure 2, considering the key influencing factors in Table 3 and printer specifications in Table 4, the first step in the feasibility analysis is to compare the estimated product dimensions with the build volumes of the available printers. Since the tool's dimensions fall within the capabilities of both printers, it satisfies this condition. Next, the compatibility of the printers with available materials is investigated. Both printers are compatible with the listed materials, so this condition is also met.

The material properties are then compared against the product's criteria and requirements. The requirements of the product do not indicate any limitations for the application of the available printing material at this stage. For instance, while properties such as tensile strength and Young's modulus alone are not fully representative of all relevant factors, they currently show no limitations for supporting the required load of 3 kg. Based on this preliminary analysis, AM appears feasible for this application.

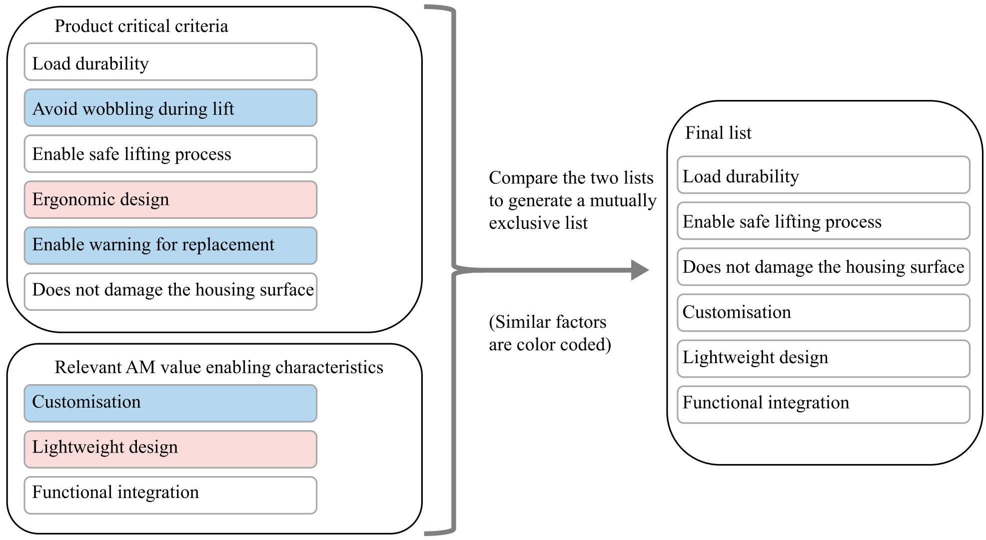

Figure 6. Comparison of product critical criteria and requirements with AM value enabling characteristics.

5.3. Suitability analysis of AM

For the suitability analysis of AM, as both Ultimaker S7 and Prusa i3 MK3S are material extrusion printers with similar characteristics, an average value for this printer type is used. The AM process is compared against the conventional method for producing similar products, which involves casting and machining, using steel as a primary material. The procedure for suitability analysis follows the process explained in Section 4.3.

5.3.1. Comparison of product critical criteria and requirements with AM value enabling characteristics

As highlighted in Table 3, important criteria and requirements, and the AM value-enabling characteristics are classified into two different categories. These two lists are not mutually exclusive. For example, preventing wobble can be achieved by designing grips on the body of the tool, and the replacement indicator can be designed by incorporating grooves similar to those found on vehicle tyres. These features are made possible through customisation, one of the key advantages of AM. In this example, customisation serves as a more inclusive factor, replacing the two other factors explained. Similarly, ergonomic design shares similarities with the lightweight characteristic enabled by AM. As ergonomic design itself can be partially included in customisation, lightweight will remain representative in this case. The final list of criteria and AM value-enabling characteristics are illustrated in Figure 6.

5.3.2. Estimation of lead time and cost for the AM process

Estimation of lead time for the AM process

Given the tool's dimensions, the AM manufacturing time for a single unit is estimated to be 10 h (T_1). When the additional processing time is considered, the total lead time for one unit (T_{lead}) is estimated to be 30 h. The total production time for all 13 units (T_n) is calculated at 130 h. Including setup and other related activities, the lead time for the entire

Table 5. Density and price of available polymers for printing, prices extracted from 3D Prima (2024).

Material	Density (g/cm^3)	Price (SEK/g)
PLA	1.25	0.19
PETG	1.23	0.28
ABS	1.04	0.22
ASA	1.13	0.39
Average:	**1.16 (g/cm^3)**	**0.27 (SEK/g)**

batch (T_{total}) is approximately 270 h. In this estimation, values for l, h, and d are considered 20 mm, 240 mm and 130 mm, respectively. Further, s is estimated to be 35 mm/s and w is considered 0.4 mm according to Table 4. The detailed calculations are provided below:

$$T_r = \frac{20\,\text{mm}}{35\,\text{mm}} \tag{15}$$

$$R_l = \frac{130\,\text{mm}}{0.4\,\text{mm}} \tag{16}$$

$$L_n = \frac{240\,\text{mm}}{0.75 \times 0.4\,\text{mm}} \tag{17}$$

considering V_f to be 0.25, based on Equation (1):

$$T_1 \approx 37{,}143\,\text{s} = 10\,\text{h} \tag{18}$$

$$T_n = 10 \times 13 = 130\,\text{h} \tag{19}$$

$$T_{lead} = 30\,\text{h} \tag{20}$$

$$T_{total} = 130 + \frac{30 - 10}{2} \times (1 + 13) = 270\,\text{h} \tag{21}$$

Estimation of cost for the AM process

Cost for the AM process is estimated based on Equation (8). Density (M_d) and cost per gram (C_w) can be considered as the average value for available printing material options, 0.27 SEK/g and 1.16 g/cm^3, respectively (see Table 5).

With an estimated 20 h of labour at a rate of 600 SEK per hour in Sweden, the associated cost is approximately 12,000 SEK, representing a substantial portion of the total cost (see Equation (24)). Assuming an average power of 0.5 kWh for material extrusion printers and an energy cost of 1 SEK/kWh in Sweden, the machine cost is estimated in Equation 25. This cost is estimated to be lower than the labour and material costs. The overall cost is calculated to be approximately 14,000 SEK, based on Equation (26)

$$M_w = 1.16\,\text{g/cm}^3 \times 20\,\text{mm} \times 240\,\text{mm} \times 130\,\text{mm} \times 10^{-3} \times 0.25$$

$$M_w \approx 181\,\text{g} \tag{22}$$

$$C_{mat} = 181\,\text{g} \times 0.27\,\text{SEK/g} \times 13 \approx 635\,\text{SEK} \tag{23}$$

$$C_{lab} = 600 \times 20 = 12{,}000\,\text{SEK} \tag{24}$$

$$C_{machine} = 130\,\text{h} \times 0.5\,\text{kW} \times 1\,\text{SEK/kWh} \approx 65\,\text{SEK} \tag{25}$$

$$C_{total} = (635 + 12{,}000 + 65) \times 1.10 \approx 14{,}000\,\text{SEK} \tag{26}$$

Influence of quality assurance and control on resource consumption

For comparison, the design and manufacture of a similar product with conventional manufacturing would take approximately six months (around 950 hours) and cost 54,000 SEK for the batch. Although this process has well-established quality assurance and control procedures, such procedures would need to be re-evaluated for polymer-based AM products, potentially affecting lead time and cost. However, this impact is not included in the current estimates for simplicity.

5.3.3. MCDM analysis

The final step involves conducting an MCDM analysis, incorporating all critical product criteria and requirements, AM value-enabling characteristics, lead time, and cost. As outlined in Section 4.3.3, the importance of each factor is determined by the user. For instance, cost may be prioritised over the possibility of functional integration. In this example, the weights were elicited based on observations made and subsequent discussions with the project coordinator. However, to maintain commercial confidentiality, the numbers were changed slightly. However, this does not affect the insights drawn.

The performance of the AM process, using polymer material extrusion, is then compared to that of the conventional manufacturing process, which involves casting and machining steel. While AM offers greater opportunities for customisation, the use of the conventional method may provide superior durability due to the use of metal. The estimated lead times and costs for both processes–270 h and 14,000 SEK for AM, versus 950 hours and 54,000 SEK for conventional methods–are used to assign the relevant scores in the MCDM analysis. Table 6 summarises the analysis, considering a value of 570 for the ideal manufacturing process, which receives 10 for all factors. AM achieves a suitability score of approximately 73%, indicating that, based on the information provided and analysed, it can be a more appropriate manufacturing alternative compared to CM (scoring 50%) for manufacturing the product.

To assess the robustness of the method, a sensitivity analysis was conducted by increasing the weight of each factor by 10% individually, while keeping all other weights constant. Using these adjusted weights, the suitability percentages for AM and CM were recalculated. The results, presented in Table 7, indicate that the suitability of AM remains around 70% while CM maintains a value of 50%. This confirms that AM consistently remains more suitable than CM across different weight variations, confirming the stability of the decision-making method.

Table 6. MCDM analysis based on weighted sum model for example of the lifting tool.

Factors	Weight	Score of AM	Score of CM
Load durability	9	3	9
Safe lifting process	9	6	9
No damage to the surface	7	7	4
Customised design	7	9	4
Lightweight design	6	9	5
Functional integrated design	2	9	3
Lead time	8	9	2
Cost	9	9	2
Total score		418	288
Percentage of suitability		**73**	**50**

Table 7. Results of sensitivity analysis, where weight of each factor was individually adjusted while keeping others constant, to assess the impact on the suitability percentage of AM and CM.

Factors	Original Weight	10% weight Change	Score of AM	Score of CM
Load durability	9	9.9	72.7	51.1
Safe lifting process	9	9.9	73.1	51.1
No damage to the surface	7	7.7	73.3	50.4
Customised design	7	7.7	73.5	50.4
Lightweight design	6	6.6	73.5	50.5
Functional integration	2	2.2	73.4	50.4
Lead time	8	8.8	73.6	50.1
Cost	9	9.9	73.6	50.1

6. Discussion

In this paper, three research questions are explored and discussed separately.

RQ1: What key factors available in the pre-conceptual design phase determine the suitability of AM?

To address this question, the importance of considering factors related to both the product and its surrounding ecosystem is emphasised. Various relevant factors are discussed, such as the importance of considering product criteria, value-enabling characteristics of AM and process-related factors, including process constraints related to lead time, cost, and other factors. Sustainability emerges as a critical factor, including both product and process dimensions. This complex issue extends beyond CO_2 calculations and often requires consideration of risk and alternative strategies.

Comparing these findings with the existing literature, very few studies have identified all the important factors. For instance, Douglas C. Eddy, Krishnamurty, and Steudel (2019) incorporated key factors such as design criteria, AM value-enabling characteristics and manufacturing cost. However, the influence of quality assurance and control procedures on the overall time and cost assessment is not accounted for. Similarly, Schuhmann et al. (2022) introduced a method that includes important factors such as AM value-enabling characteristics, resource constraints and production volume, but does not directly consider design criteria such as load durability, structural flexibility or surface roughness characteristics.

RQ2: How can these factors be integrated into a method to guide designers in evaluating the suitability of AM before design commences?

The available methods for determining the suitability of AM in the pre-conceptual design phase have notable gaps. Some methods only assist in the feasibility analysis of AM processes and materials (e.g. Ashby 2005; Lovatt and Shercliff 1998; Swift and Booker 2013). While these methods help to eliminate unfeasible options, they do not directly aid in evaluating AM suitability. Selecting the appropriate manufacturing process late in the design phase often limits the application of design for manufacturing guidelines, including DfAM. This can result in suboptimal outcomes.

To address this, MPDS is designed to have two main components: first, a feasibility analysis of AM, and second, an assessment of AM suitability. The novelty of MPDS suitability analysis lies in the integration of product- and process-related factors, which are often overlooked in the available methods. Additionally, MPDS provides a structured, step-by-step guide for users to identify and evaluate the relevant factors.

RQ3: What are the benefits and limitations of the proposed method?

In product development, it is often recommended to explore the design space extensively and keep alternative solutions open for as long as possible, progressively narrowing down choices based on constraints. However, AM diverges from this traditional approach, as it requires early commitment in the design phase to fully leverage its advantages. Delaying the decision to employ AM can lead to suboptimal outcomes or necessitate additional design iterations, resulting in increased costs. Current industrial practices often postpone the decision to adopt AM until late in the design cycle or even after the design is finalised. This delay frequently results in missed opportunities to leverage the full potential of AM, posing a significant barrier to its broader adoption. Therefore, structured decision-support tools such as MPDS are crucial for enabling well-informed choices in the pre-conceptual design phase, maximising the benefits of AM while minimising risks associated with late-stage design changes.

Early integration of feasibility and suitability assessments in the design process enables informed decision-making while design flexibility is still high. Identifying the suitability of AM at this stage allows engineers to adapt designs to fully leverage the advantages of AM, such as lightweight design (Tempelman 2014) through methods such as topology optimisation or reduced part numbers via functional integration. The consideration of feasibility and suitability analyses of AM in the early product development process can provide the opportunity to optimise performance and enhance manufacturability. An iterative approach ensures alignment between design and manufacturing strategy, reducing late-stage modifications and associated cost escalations.

While only a few guidelines are already available, MPDS enables a transparent and logical decision-making process to investigate the feasibility and suitability of AM early in the design phase. In this study, the MPDS was applied to compare a single AM process with one conventional manufacturing process, for the sake of simplicity. However, the methodology is inherently flexible, as it is based on MCDM analysis, and can accommodate comparisons among multiple manufacturing alternatives. This approach is expected to significantly contribute to the broader adoption of AM in the industry by enabling early, well-informed decision-making, which maximises the advantages of AM and minimises the risks associated with late-stage design changes or suboptimal manufacturing choices

Despite its strengths, the MPDS methodology has limitations. As this method is intended to be used in the pre-conceptual design phase, limited information is available both about the product and the process, which inevitably deals with uncertainty. For instance, estimating lead time and cost for the AM process is challenging as design and printing setup can have a high impact on manufacturing time and cost. Similarly, estimating lead time and cost for conventional manufacturing can be challenging as past manufacturing experience does not always accurately predict future outcomes in terms of lead time and cost.

Another notable limitation is the exclusion of sustainability considerations, despite their importance, as indicated by the first research question. Incorporating sustainability into the decision-making process requires further research to refine the methodology. Additionally, the methodology relies on user input, which introduces a degree of subjectivity. User judgments directly influence the results, and any errors in scoring can distort the analysis. Furthermore, the absence of a mechanism to integrate data from previously designed and manufactured products is a missed opportunity, as incorporating past successes or failures could enhance accuracy and reduce subjectivity. Looking ahead, ML techniques could be employed as they help the system evolve and learn over time to make more informed and effective decisions.

7. Conclusion

In order to fully benefit from any manufacturing process, the product needs to be designed specifically for that manufacturing process. Deciding late on the manufacturing process leads to suboptimal results or sometimes requires redesign, wasting resources and causing late delivery. As AM is still considered a new technology in many sectors, designers need to know ‘when’ to design for AM instead of traditional manufacturing processes. Deciding on the manufacturing process in the pre-conceptual design phase, before the availability of detailed geometry, is often overlooked in both academia and industry, despite an increasing need for it in practice.

A lack of suitable guidelines for assessing both feasibility and suitability of AM early in the design phase often leaves designers to make these decisions intuitively, which hinders broader industrial adoption of AM. To address this gap, key factors that should be considered for evaluating the suitability of AM are identified, both in terms of the product and the process. Based on these factors, the MPDS has been developed as a guideline to assist designers with this assessment early in the design phase. This development is intended to close the gap in existing guidelines, facilitating more informed decision-making and supporting AM’s broader industrial adoption. An example demonstrating the application of MPDS for a lifting tool is also presented.

For future work, two main directions are proposed. In the short term, MPDS should be developed into a user-friendly tool and validated by designers to test its practical effectiveness. In the long term, two avenues for improvement are suggested: (1) a deeper exploration of how sustainability can be incorporated into the decision-making process, and (2) advancing decision support to improve decision-making, for instance, through the application of AI techniques. AI could add value by providing smart suggestions regarding factor inputs and AM suitability. For instance, leveraging ML can facilitate benefits from past manufacturing experiences. Additionally, AI could speed up the decision-making process, for instance, by employing natural language processing (NLP) to automatically extract key factors from product specifications, thereby reducing manual work.

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