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Selecting spare parts suitable for additive manufacturing: A design science approach

Abstract:

Additive manufacturing (AM) can help to deliver spare parts within short lead times and thus avoid maintaining huge inventories. Companies exploring opportunities to produce spare parts using AM face challenges in identifying suitable spare parts to be produced. Moreover, a single method may not be applicable for all companies and needs to be adapted considering the characteristics of the parts in the portfolio. This study follows a design science approach to addresses an evident research gap by developing a process to identify spare parts suitable for AM. The case data was analyzed using multi-criteria decision-making and cluster analysis techniques. The research contributes by developing and demonstrating a methodology to identify spare parts suitable for AM from a portfolio of a large number of spare parts, where adequate discrimination was not obtained by ranking all parts together. The study develops generic guidelines for spare parts selection for AM and outline the generalizability of the proposed methodology beyond the domain of part selection for AM.

Keywords: Additive manufacturing, Spare parts selection, Multi-criteria decision-making, Cluster analysis, Design science

1. Introduction

Managing spare parts can be challenging due to intermittent demand patterns that makes forecasting a difficult task (Van der Auweraer and Boute, 2019). Furthermore, the high service level requirements needed to avoid the high cost of downtime for customers makes spare parts planning even more complex. Therefore, companies tend to keep high levels of inventories of spare parts in different locations in order to meet service level requirements (Ghadge et al., 2018). Additive manufacturing (AM) can help firms cope with this complexity by overcoming some of the above challenges (Khajavi et al., 2014; Li et al., 2017; Frandsen et al., 2019). AM is promising as a technology for spare parts production as it can handle the challenges of high variability, long lead times, low demand, and high stock-out costs associated with traditional manufacturing of spare parts.

Prior research has outlined the benefits of AM for producing spare parts. For instance, Li et al. (2017) show that producing low volume spare parts using traditional manufacturing, as compared to using AM, results in higher supply chain costs and higher carbon emissions. Thus, AM allows companies to move low volume products away from the traditional manufacturing setting. By removing low volume and disruptive parts from regular production methods, AM can increase service levels via the timely availability of spare parts (Sasson and Johnson, 2016; Ghadge et al., 2019). Other benefits of using AM include reduction in safety stock due to on-demand use of direct manufacturing (Liu et al., 2013; Tziantopoulos et al., 2019) and reduction in unit costs due to lower transportation costs, as AM allows for production at distributed locations which are closer to the locus of demand (Li et al. 2017; Khajavi et al., 2014). Use of AM for spare parts production also helps in supporting the maintenance process of capital goods throughout their lifecycles, which often spans across several decades (Knofius et al., 2016). Using the F-18 Super Hornet's service supply chain as an example, Holmström and Partanen (2014) report that hybrid solutions, which combine conventional logistics, digital manufacturing and user operations, provide direct benefits of extending the life cycle and increasing availability of spare parts to serve challenging locations. Using system dynamics simulations, Li et al. (2017) show that spare part supply chains using AM were, indeed, superior to traditional manufacturing supply chains with respect to sustainability performance. Similarly, Ghadge et al. (2018) show that AM can help balance inventory levels and increase responsiveness, while decreasing disruptions and carbon emissions in the spare parts supply network.

From the above-mentioned literature, it is apparent that adopting AM for spare parts production and designing a suitable AM spare parts supply chain could have multiple potential benefits including reduction in costs, improved availability, and lower carbon emissions. However, there are multiple challenges associated with the adoption of AM for spare parts production, which include limited size of possible components, inadequate quality, and variable quality across AM equipment. In addition, there is variance in quality of AM materials which makes it difficult to generate 3D models especially from components that are obsolete. Also, violation of intellectual property rights (Chekurov et al., 2018) and post-processing requirements (Kretzschmar et al., 2018) are additional examples of obstacles that prevent widespread use of AM.

Many industrial manufacturers, including the case company considered in this research, face challenges of ensuring availability of spares at the right time, while reducing the inventory holding costs and costs associated with low volume production. Such companies have considered using AM as an opportunity for spare parts production. Nevertheless, for companies which are willing to explore AM for spare parts production, a major challenge is selecting the appropriate spare parts which can be produced using AM. It is an imperative that a systematic approach be followed to facilitate the selection of spare parts that are suitable for AM by considering both technical and supply chain aspects (Lindemann et al., 2015).

There has been limited research that offers a comprehensive approach for selecting spare parts that are suitable for AM (Frandsen et al., 2019). Notable exceptions include the works of Lindeman et al. (2015) and Knofius et al. (2016). Lindeman et al. (2015) provide an approach for parts selection which also includes exploring redesign options. Their approach relied on feedback from experts in a focused workshop setting. However, the proposed approach could only be applied to a limited number of parts. Knofius et al. (2016) apply the Analytic Hierarchy Process (AHP) to select the most suitable spare part candidates among a large portfolio of spare parts. Both Lindemann et al. (2015) and Knofius et al. (2016) make valuable contributions to the body of knowledge on parts selection for AM; however, the spare parts portfolio of a large manufacturing company can be quite diverse and following the approach suggested by Knofius et al. (2016) may not result in adequate discrimination amongst parts. By omitting to analyze the characteristics of this diverse set of parts, it may not be feasible to distinguish among the parts adequately. Hence, many companies with a large portfolio of spare parts with widely varying characteristics may need a different approach, combining the strengths of both the approaches while considering different characteristics of the parts in the portfolio to screen and score the parts. Hence, developing an approach for spare parts selection for AM by combining both a data-driven 'top-down' and expert opinion-driven 'bottom-up' approach is needed. Such an approach, with demonstrated utility in real-life application settings and particularly where limited discrimination is obtained by ranking all the parts together, is lacking in the current literature. To address this gap, the study raises a research question: ***How to select spare parts from a large portfolio of diverse spare parts for AM*?**

The rest of the paper is structured as follows. Section 2 discusses literature on the use of AM for spare parts, and part selection for AM. Section 3 discusses the approach followed for collecting and analyzing data from the selected case company. A brief background on the choice of a Multi Criteria Decision Making (MCDM) and clustering approach is also provided. A systematic process for selecting parts suitable for AM by following a design science approach applied to a case company is discussed in section 4. The results and the generalizability of the proposed methodology are discussed in Section 5. Key contributions, limitations and future research opportunities are discussed in section 6.

2. Literature review

2.1 Use of AM for spare parts production

AM has a promising potential for manufacturing low-volume components at low cost. However, not all manufacturing techniques can be substituted with AM (Lindemann et al., 2015). In many cases, characteristics such as rigidness, surface quality, dimensions, tolerances, and types of materials can pose constraints for the use of AM. An in-depth knowledge of component structure and composition is required *a priori* in order to evaluate a component's suitability for AM (Huang et al., 2012; Lindemann et al., 2015). AM should be seen more as a learning process, as opposed to the 'Plug and Play' solution that many companies expect to have for 'ready-to-build' parts to work seamlessly from the beginning (Lindemann et al., 2015).

2.1.1 Advantages of producing parts using AM

AM could be effective in reducing inventories (Holmström et al., 2010; 2014; Liu et al., 2014; Durach et al., 2017; Ghadge et al., 2018) because spare parts can be produced as and when needed within a short lead time. Also, AM has been shown to reduce lead time (Oettmeir and Hofmann, 2016; Muir and Haddud, 2017), partly due to avoiding the physical order generation process in which orders are generated by sharing digital files (Oettmeir and Hofmann, 2016). Other reasons are due to changing the locus of the decoupling point closer to the customer (Durach et al., 2017), or by reducing the number of steps in manufacturing. Similarly, AM can also help in reducing supply risk for spare parts, where low demand parts can be printed if a supplier for a traditionally manufactured part is not able to deliver in such low quantities (Knofius et al., 2016). AM can also result in decreased energy costs and improved sustainability (Gebler et al., 2014; Holmström et al., 2017).

Parts produced using AM can also have superior quality in comparison with conventional manufacturing because of better functionality, and an optimal strength-to-weight ratio (Stansburya and Idacavage, 2016; Eyers and Potter, 2017). Adopting AM can also result in lower manufacturing costs for mixed builds at full capacity (Baumers et al., 2017), lower transportation costs (Wagner and Walton, 2016), and overall lower operating costs because the distributed spare parts production uses smaller and more automated equipment (Khajavi et al., 2014), and can enable mass customization (Shukla et al., 2018). Spare parts produced by AM can also be easily replaced as production and delivery lead times can be shortened. Furthermore, AM can be used to repair portions of damaged parts instead of replacing entire parts as demonstrated successfully by Siemens Gas Turbine for repairing burner tips (Varley, 2019) and by Deutsche Bahn for fuel tank caps and other parts (Brickwede, 2017). This will reduce both cost and lead time for spare parts replacement.

2.1.2 Technical parameters for spare part selection for AM

It is important to identify the relevant criteria while selecting parts suitable for AM (Knofius et al., 2016). Parameters considered for screening and scoring parts suitable for AM can be size of parts and build volume (Lindemann et al. 2015 and Knofius et al., 2016) as parts exceeding build volume of AM equipment cannot be produced. The choice of appropriate materials which can be used for AM and which help meet the products' performance requirements is also an important consideration (Stansburya and Idacavage, 2016; Wang et. al., 2017; Lee et. al., 2017; uz-Zaman et al., 2018). Since only a limited number of materials can be used for AM, material characteristics must be considered while determining which parts can be produced using this method. Other technical characteristics which need to be considered include water resistance, temperature resistance, post-production shrinkage (Lee et al., 2017), strength-to-weight ratio, stiffness-to-weight ratio (uz-Zaman et al., 2018), and dimensional accuracy (Wang et al., 2017). As the intended spare parts are supposed to work under certain conditions, and must have the dimensional accuracy as specified, the above requirements have to be fulfilled irrespective of the manufacturing method being considered. Other technical parameters which affect the quality and productivity of the AM process are build-speed, layer thickness (Mancanares et al., 2015), support materials, machine cost, as well as the requirements for post-processing (uz- Zaman et al., 2018).

2.1.3 Supply chain, maintenance and financial parameters relevant for spare parts selection for AM

As spare parts tend to have diverse technical, maintenance, and supply chain characteristics, these need to be classified according to those characteristics for any decision pertaining to spare parts planning, including assessing the suitability for AM. There is also a large body of literature available concerning the classification of spare parts. Supply chain related parameters to classify spare parts include lead time, availability of suppliers, demand pattern (Huiskonen, 2001; Molenaers et al., 2012; Lolli et al., 2014 and Sarmah and Moharana, 2015), and obsolescence and lifecycle stage (Roda et al., 2014). Typical maintenance related criteria include criticality with respect to downtime costs, time to respond to failure, predictability of failure and maintenance type (Huiskonen, 2001; Molenaers et al., 2012). Financial characteristics which are commonly used to classify spare parts are average unit cost (Hadi-Vencheh, 2010; Lolli et al., 2014) and annual consumption value (Hadi-Vencheh, 2010; 2011; Lolli et al., 2014; Sarmah and Moharana, 2015). Chekurov et al. (2018) include size, criticality, demand pattern, complexity, value, delivery time predictability, specificity and lifecycle stage as properties affecting viability of digital spare parts. Frandsen et al. (2019) have found from their review that the most commonly used criteria to classify spare parts are lead-time, unit cost, criticality, annual dollar usage, and demand. From this review it is evident that a classification scheme based on multiple supply chain, maintenance, and financial considerations is necessary for selecting spare parts that are suitable for AM. A summary of the literature summarizing these parameters is shown in table 1.

Table 1: Summary of literature on factors used for spare parts selection for AM

Technical parameters	**References**
Size of parts	Lindemann et al., 2015; Knofius et al., 2016; Chekurov et al., 2018
Build volume	Lindemann et al., 2015; Knofius et al., 2016
Appropriate material	Stansburya and Idacavage, 2016; Wang et. al., 2017; Lee et. al., 2017; uz-Zaman et al., 2018
Water and temperature resistance	Lee et al., 2017
Post-production shrinkage	Lee et al., 2017
Strength to weight ratio and stiffness to weight ratio	uz-Zaman et al., 2018
Required dimensional accuracy	Wang et al., 2017
Build speed and layer thickness	Mancanares et al., 2015
Support materials and post processing	uz- Zaman et al., 2018
Supply chain, maintenance and financial parameters	**References**
Lead time, demand pattern and availability of suppliers	Huiskonen, 2001; Molenaers et al., 2012; Lolli et al., 2014 and Sarmah and Moharana, 2015; Chekurov et al., 2018; Frandsen et al., 2019
Obsolescence and lifecycle stage	Roda et al., 2014
Downtime costs, time to respond to failure, predictability of failure and maintenance type	Huiskonen, 2001; Molenaers et al., 2012
Annual consumption value	Hadi-Vencheh, 2010; 2011; Lolli et al., 2014; Sarmah and Moharana, 2015; Chekurov et al., 2018; Frandsen et al., 2019

2.2 *Approaches for selecting spare parts suitable for AM*

The extant research reports multiple approaches or techniques for classification of spare parts. These include pairwise comparison, a distance-based method, outranking, compromise ranking, weighted linear optimization, and rule-based decision making. In particular, data-driven as well as expert-driven approaches have been suggested in this literature. The data driven approach brings objectivity to the selection process but requires the availability of data. The need for an expert-driven approach arises because many companies may not have the requisite data pertaining to the different characteristics to conduct the assessment. The data that are available reside in various software systems and cannot be accessed at the same time. In other instances, for example, the drawings of the parts may not be available in a digital form. Different spare parts classification criteria need to be considered while taking into account the specific application context before finalizing the most appropriate method for selecting spare parts most suitable for AM (Frandsen et al., 2019). Therefore, the choice of approach to be used will depend on the objectives from the exercise, and availability of data.

2.2.1 Expert driven bottom-up approach for spare part selection for AM

When evaluating eligibility of parts for AM, it is important to take all the interfaces and functionalities of each component into account, as well as consider redesign opportunities, if necessary (Lindemann et al., 2015). In this regard, Lindemann et al. (2015) propose a methodology in which the selection of parts is divided into three phases: Information, Assessment and Decisions.

The methodology proposed by Lindemann et al. (2015) can be described as a bottom-up workshop approach for evaluating AM. In this approach, with the help of input from practitioner/experts, an assessment of the benefits and feasibility to print the part using AM can be made based on the characteristics of the part. However, this assessment approach only considers a limited number of parts and factors. Therefore, some potentially eligible parts may be overlooked. Also, this method does not take into account factors such as supply lead-time, safety stock, holding costs and obsolescence risks.

2.2.2 Data driven approach for spare parts selection for AM

The challenges associated with the bottom-up approach can be avoided by using an alternative top-down approach (Knofius et al., 2016). In this approach, parts are evaluated based on potential economic benefits, thereby minimizing the risk of disregarding promising parts. This alternative approach is less dependent on the expertise of managers, which reduces the risk of underestimating logistical improvements and capturing full life-cycle costs. This approach incorporates three steps:

- Determining the spare part assortment
- Obtaining the weights attached to attributes of spare parts
- Calculating the overall score of a spare part

This method increases the transparency in the decision-making process of deciding which spare parts could benefit from additive manufacturing (Knofius et al., 2016). In particular, this approach can be used to simplify the identification and prioritization of promising spare parts.

For a data-driven approach of spare parts selection for AM, it is necessary to classify the spare parts. From the traditional single-criterion ABC-classification based on annual dollar usage (average unit price x annual demand volume) to the advanced multi-criteria methods, a wide range of classification schemes have been proposed in the spare parts literature (e.g., Bhattacharya et al., 2007; Chen, 2012). Such methods can also be used to classify spare parts, that are suitable for AM.

2.3 Summary of literature review

Although a large body of literature exists on spare parts classification, clearly, there is limited literature on the topic of selecting spare parts that are suitable for AM. There is a need to identify the appropriate technical and supply chain related factors which can be used to classify and identify the spare parts that are suitable for AM. More importantly, there is a need to develop suitable approaches which can help a company analyze their large portfolio of spare parts, and determine the most suitable parts which can be produced by AM. Without such an approach, companies face challenges in adopting AM for spare parts manufacturing. The bottom-up approach, as suggested by Lindemann et al. (2015), can only consider a limited number of parts for evaluation while the method proposed by Knofius et al. 2016 may not guarantee adequate discrimination of parts for the spare parts portfolio of all companies.

This study attempts to address the need of industry, as well as gaps in the academic literature on this topic by identifying a suitable approach to select spare parts that are suitable for AM, from a large portfolio of parts, *where suitable discrimination cannot be obtained by scoring all parts together*.

3.0 Methodology and data collection

3.1 Design Science as an overarching approach to address the problem

Design science allows researchers to be actively engaged in problem solving while still developing scientific contributions. While both action research and design science involve active problem solving by the researchers, action research does not explicitly result in an 'artifact' contrary to design science (Holmstrom et al., 2009). Design science follows four phases: 1) solution incubation; 2) solution refinement; 3) explanation through substantive theory; and, 4) explanation through formal theory. Solution incubation starts with understanding the problem and developing the first solution design, which is detailed enough to be implemented but may be incomplete. Solution refinement includes refinement of the initial solution design through iterations and to verify what works and what does not and, thus, includes design improvements, implementation and evaluation. This phase may also involve addressing unintended consequences. To proceed beyond problem solving, the researcher tries to evaluate the developed artifact from the theoretical point of view and focuses on development of a substantive theory which is a context dependent theory developed for a narrowly defined context and empirical application. The final phase involves development of a formal theory, if possible, which is aimed at broader generalizability (Holmstrom et al., 2009). As the objective of this research is to solve a problem faced by the company by developing a process or an artifact and to generalize the findings for a theoretical contribution, we adopted a design science approach.

3.2 Selection of multi-criteria decision making methods

While classifying and ranking spare parts suitable for AM, several factors have to be considered, for which multi-criteria decision making (MCDM) approaches are found to be suitable. Several MCDM methods such as AHP (Saaty, 1990), Analytic Network Process (ANP), TOPSIS (Yoon, 1987), VIKOR (Duckstein and Opricovic,1980), ELECTRE (Benayoun et al., 1966), and Preference Ranking Organization Methods for Enrichment Evaluation –PROMETHEE (Brans and Vincke, 1985) can be used to classify and select spare parts that are suitable for AM. MCDM methods like AHP, TOPSIS, VIKOR, PROMETHEE and ELECTRE III work under the condition that input criteria can be scored independently against objectives, without considering the configuration of other criteria. Therefore, the above methods are not applicable when there are interdependencies amongst the criteria. To manage interdependencies, ANP can be used. This method requires pairwise comparisons.

TOPSIS is a method of compensatory aggregation which compares alternatives based on weights for each criterion, which then are normalized in order to calculate the geometric distance between each alternative relative to the ideal alternative and farthest from the negative ideal alternative. TOPSIS selects the alternative which is farthest from the negative ideal alternative and closest to the ideal alternative (Yoon, 1987). However, TOPSIS does not rank the criterion in a hierarchy and thereby needs less input from decision-makers.

The VIKOR method focuses on ranking and selecting from a set of alternatives in the presence of conflicting criteria. It determines a compromise solution that could be accepted by the decision makers because it provides a maximum group utility for the ''majority'' and a minimum of individual regret for the 'opponent''. In comparison, the TOPSIS method introduces two reference points, using vector normalization, but it does not consider the relative importance of the distances from these points. Ranking using the PROMETHEE method, with a linear preference function, gives the same results as ranking using the VIKOR method. Ranking results using the ELECTRE II method, with linear ''surrogate'' criterion functions, are relatively similar to the results using the VIKOR method (Opricovic and Tzeng, 2007).

To decide on which method to apply, conceptual and operational validation of the application of a method to real world problems is needed. Researchers should choose the method that is both theoretically well founded and practically operational to solve actual real world problems (Opricovic and Tzeng, 2007). AHP can be used on small criterion sets and TOPSIS can be used on large criterion sets (Özcan et al., 2011). However, Zanakis et al. (1998) show that TOPSIS has performed better than AHP for small criterions sets as well.

Pairwise comparison of a large number of parts on multiple factors was considered infeasible for the AM part selection problem, thus ruling out AHP, ANP, ELECTRE and PROMETHEE for ranking of spare parts. As no single part can be considered ideal with respect to all factors needed for assessing suitability with respect to AM, distance from the most ideal part and the least ideal part as used in TOPSIS was found to be the most suitable approach.

3.3 Choice of clustering method

A large dataset may have spare parts with different characteristics and trying to rank all of those together may not result in 'like-to-like' comparisons. Clustering the spare parts can help in classifying them, and hence the clusters, and parts within those clusters that are most suitable for AM can be identified. Mooi and Sarstedt (2011) present three clustering methods, which are used for different scenarios:

1. **Hierarchical clustering:** If the data set is < 500 data points
2. **k-means clustering:** If the data set is > 500 data points
3. **Two-step clustering:** If the data set is > 500 data points and the clustering variables are measured on different scale levels

The hierarchical clustering method generates a series of models with cluster solutions from one cluster to n clusters. Hierarchical clustering is only used for small data sets, as the computing power required is of the order of O(n3) (cubic time), compared to, for example, for k-means the computing power required is of the order of O(n2) (quadratic time) (Mooi and Sarstedt, 2011). The k-means clustering method can effectively cluster complex data sets. The number of clusters are decided in advance, and the algorithm works iteratively to assign each data point to one of the clusters based on similarities of the features. Two-step cluster analysis (TSCA) is able to handle large data sets with mixed variables, that are on different scales (e.g., categorical and continuous, dollars and kilograms) (Mooi and Sarstedt, 2011). TSCA is based on two steps:

1. ***Pre-clustering:*** An algorithm closely related to k-means clustering is used to create pre-clusters called 'dense regions'
2. ***Modified hierarchical agglomerative clustering:*** Where it combines the pre-clusters sequentially to form homogeneous clusters

3.4 Data collection

The primary source of data used in this research was accessed via semi-structured interviews and through feedback from senior managers at the case company following a focused workshop. The interviews were with two key informants in the company, who were responsible for global procurement of materials and components (Senior Managers, Global Category Management). In total, seven meetings with company representatives were held. These meetings had a duration of two to three hours, over a three-month time period. Five of the authors participated in all interviews.

Interviews with the contact persons was necessary in order to 'scope out' the project, to provide status updates, obtain feedback and validate the results. Interviews were held at the case company. The interviews were part of regular status update meetings with the company, and questions were asked to clarify any issues that the research team had as they progressed with their research.

These issues pertained to: 1) setting up screening criteria and justification for those criteria; 2) sharing the results of the screening process; 3) sharing results of initial scoring and obtaining feedback; 4) explaining the need for conducting the cluster analysis; 5) sharing results of cluster analysis and obtaining feedback; 6) sharing ranking of parts within clusters and ranking of clusters and validating them, which was followed by requesting drawings and obtaining clarification on doubts, if any; and 7) sharing of the framework.

The workshop was used to define and prioritize the objectives. The workshop participants were the two key informants in the company, two other employees working in spare parts planning within the case company, and five co-authors. It is important to emphasize that the research team was in constant dialogue with the key informants in the case company. Our research team had a series of meetings with company representatives as described above during the entire research. Our research was conducted in an 'action research' mode, with the research team addressing all problems pertaining to selection of parts suitable for AM with the case company.

4.0 Selection of spare parts suitable for AM in the case company

The case company manufactures floor care products, high pressure washers, vacuum cleaners, and spare parts for the above products. The company guarantees availability of spare parts for maintaining the products that they sell. The duration of these service guarantees is usually more than 10 years. The company faces key challenges in guaranteeing availability of spare parts due to unsatisfactory service levels and high cost of low volume spare parts. The company is exploring the possibility of using AM for spare parts to overcome these challenges. Examples of parts used by the OEM in its products include valves, filters, hoses, gaskets, brackets, sensors, rubber blades, bushes, plugs, caps, seal holders, joints, supports, roller guides, and mufflers. The majority of these parts were polymer parts. We follow a design science approach and propose an "artifact" i.e., a part selection process as a "means to an end" to address the problem (Holmstrom et al., 2009).

The steps followed in selecting the spare parts, which are most suitable for AM are shown in figure 1. The first step of the proposed method is to inform the case company about the benefits and limitations of AM. In the second step, the objectives of implementing AM and their relative importance (expressed as weights) are defined by the case company using pair wise comparison. In the third step, spare parts are screened based on whether those parts can be produced using AM based on technical characteristics. The technological characteristics considered as relevant by the case company were material, dimensions, weight, and tolerance. As details about materials, weight and tolerance were not available for the entire spare parts portfolio within the same IT system, or in an easily accessible format, initial screening was done only based on the characteristic of dimensions. We initially ranked all spare parts together after initial screening as a solution incubation step within a design science approach but faced the unintended consequence of limited discrimination of parts. Hence, we went ahead with solution refinement and, in the fourth step, the spare parts were assessed based on demand, lead time, and overhead costs (inventory and transportation cost) by clustering the spare parts on the above dimensions. In the fifth step, clusters are ranked and a sample of parts to be drawn from each cluster is determined as availability of technical drawings of all parts are limited. In the sixth step, parts within each cluster are ranked. Finally, spare parts, screened and selected for further analysis based on previous steps, are assessed based on materials, weight and tolerance using technical drawings.

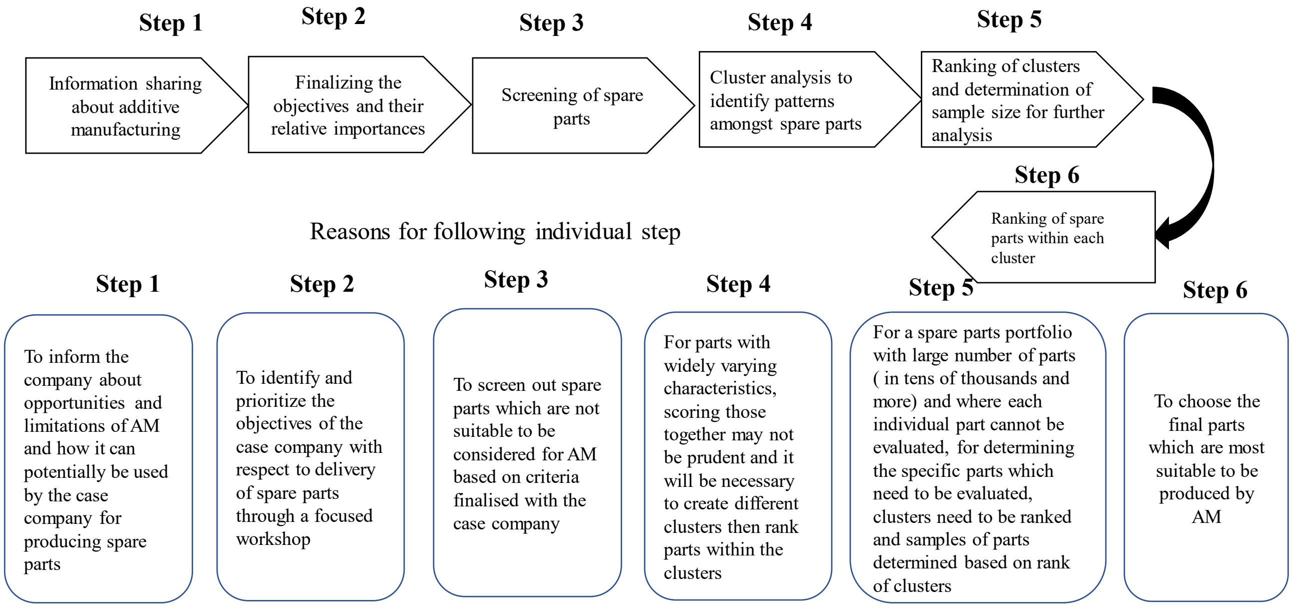

Figure 1: Steps followed in selecting the spare parts, suitable for AM

4.1 Information sharing and clarifying objectives

The first step is sharing information regarding AM. In this step, the case company was informed about the advantages and limitations of AM. The possibilities of using AM and how it might be a suitable manufacturing alternative for manufacturing spare parts at the case company was discussed. Furthermore, reports from the Port of Rotterdam (2016) and Salmi et al. (2018) were presented to the case company, as these reports depicted how AM was used for spare parts by other companies. These reports portray the technology behind AM, and how they can influence the service and cost trade-off. This was done in order to create the best possible foundation for defining objectives of implementing AM for spare parts.

The next step was to define the case company's objectives for implementing AM. An important aspect when defining objectives was to secure clarity and coherence between the capabilities of AM and the defined objectives of implementation. The objectives were finalized through a focused workshop involving the two key informants in the company, two other employees working in spare parts planning within the case company, and five co-authors. Thus, the agenda of the workshop was to identify the objectives of the company with respect to delivery of spare parts and to prioritize those objectives.

In the context of spare parts for the case company, service was defined in terms of quality, availability, and lead time. Therefore, spare parts were required to be produced to the customer's quality and lead time requirements, along with making parts available in the right quantities. Cost comprised different important elements including unit cost, inventory cost, and obsolescence. Other objectives comprised obtaining knowledge within AM as well as developing a new business model to mitigate supplier risk. The three objectives were then compared pair-wise in order to obtain relative weights using AHP. The results of the analysis are visualized in Figure 2.

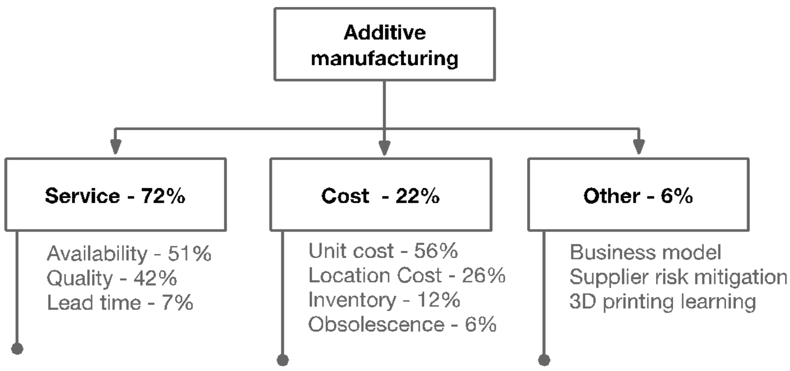

Figure 2. Weight of objectives

Results from AHP showed that service is weighted at 72%, while cost is weighted at 22% and other areas at 6%. Within service, availability is weighted at 51%, quality at 42%, and lead time at 8%. Within cost, unit cost is weighted at 56%, location cost at 26%, inventory cost at 12%, and obsolescence at 6%.

4.2 Screening of spare parts

The next step was to screen the spare parts using the parameters considered relevant for the case company and which were validated by the key informants from the company.

- **Material:** The specific material that the item is made of
- **Dimensions:** The height, width and depth of the spare part
- **Weight:** The weight of the component without packaging
- **Tolerances:** If the spare part can be produced to specifications

Since three of the technical parameters were not available from the case company in the same database, in the initial screening, sorting was done solely on the basis of the dimensions of the spare parts. The non-availability of spare part material, weight, and tolerances means that several non-printable spare parts were not removed from the data set in this step. In order to address this problem, technical drawings of spare parts were examined in step five. The technical drawings specified the material and tolerances of the sorted spare parts.

The AM materials which were considered were: PLA (Polylactic Acid), and ABS (Acrylonitrile Butadiene Styrene), PVC (PolyVinyl Chloride), and SAE 1110-1215 steel. The selected parts could be processed using fused deposition modeling (FDM), selective laser sintering (SLS), stereolithography (SLA), and polyjet. A printer database with multiple materials and AM processes was compiled by visiting the websites of all major AM equipment suppliers in order to 'short list' the feasible sets of equipment which could be considered. This list is shown in Appendix 1. The limits set, based on the printer database and by considering the size of the case company's parts, were: Height: 1000 millimeters, Width: 1000 millimeters, Depth: 1000 millimeters. This information was obtained in consultation with the key informants in the company. By setting these limits, the total number of spare parts was reduced from 64,921 to 14,252.

After screening parts based on dimensions, the parts were further screened based on 'time to stock-out' and price of the parts. 'Time to stock-out' describes the number of years'-worth of inventory that the company currently has in order to satisfy demand for each spare part. This is calculated by dividing inventory by demand (in years). Since the company has a service guarantee of 10 years and an assumption was made that if the inventory is big enough to cover the annual demand for next 10 years, then the spare part is not suitable to be considered for AM since the whole service guarantee will be covered in this time horizon using available inventory. Thus, all spare parts with a 'time to stock-out' above 10 years were removed from further consideration. In this process, 271 spare parts were removed. The average 'time to stock-out' for the removed products was 38.1 years.

Spare parts were then screened based on the overhead cost. The calculated overhead costs covered all costs relating to transport, inventory holding, and other relevant overhead costs distributed among a set of products. An assumption was made that products with an overhead cost of over 100% of the cost of the product were outliers. In this screening phase, 4,101 spare parts were removed. We acknowledge that removing the parts with overhead costs above 100% of the cost of the part is another simplifying assumption. The research team specifically analyzed those parts and discussed them with the key informants. Again, the key informants reached the conclusion that the majority of those parts have data quality issues and data entry errors, while some may, indeed, have high inventory and hence high overhead costs. We fully agree that such parts with high inventory could, indeed, be feasible candidates for AM but, as it was not possible to segregate which parts have correct overhead cost data and which had data errors, the simplifying assumption was made. The logic applied by the key informants was that since these parts already had enough inventory, there will be no benefit in producing those by AM. This also stems from the fact that this research is done from the current perspective and the company's motivation to produce the first parts using AM and demonstrate their feasibility.

The next screening phase related to removing all the spare parts which were classified as 'obsolete' in the dataset. This screening removed all spare parts which are no longer sold by the company; in this process phase a total of 1,464 spare parts were removed. Fourth screening was performed by setting the standard cost price to a maximum of 1,000 Danish Kroner (DKK). Through inspection of the data and in collaboration with the key informant in the company, it was noted that the spare parts with high standard cost price were, primarily, electronics items.

This is the first time that the company was trying to explore potential applications of AM for spare parts production. Hence, the company was interested in identifying a few feasible parts, which they could try out at first, build positive business cases so that they can gain experience and demonstrate benefits before they try out AM for other parts. Though electronic circuits can be printed, early adopting companies experimenting AM for building confidence will not go for printed electronic circuits as such experiment could be very risky. Instead, as communicated by the key informants, the company preferred to print parts which can be successfully produced along with the desired quality without much difficulty. This was the reasoning behind excluding high valued electronic parts. It was therefore agreed, in consultation with the key informants in the company, that a standard cost price of over 1,000 DKK would be the threshold for non-printable materials. Through this screening phase, 528 spare parts were removed. In the entire screening process across all the phases, a total of 6,364 spare parts were removed. The four screening steps are summarized in Table 2.

Table 2: Spare part screening

	Time to Stock-out	Overhead Cost	Obsolete	Standard Cost
Action	Removing spare parts if: inventory / demand > 10	Removing spare parts with a overhead of more than 100% of the standard cost	Remove all spare parts classified as 'Obsolete'	Removing the spare parts which have a standard cost of more than 1000 DKK
Spare Parts Removed	271	4,101	1,464	528

4.3 Solution incubation: Initial ranking of spare parts

The spare parts need to be ranked in order to determine their feasibility for AM. Initially, TOPSIS was used as a MCDM method. The criteria used for the ranking of the spare parts included lead time, demand and overhead cost.

The steps of the TOPSIS method are shown below:

The first step is to create the normalized decision matrix:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum(x_{ij}^2)}} \text{ for } i, \ldots, m; \; j, \ldots, n$$

Where:

- rij = Normalized score
- xij = Score of option i in respect to criterion j
- m = number of options = 7888
- n = number of criterion = 3

The second step is to create the weighted normalized decision matrix:

$$v_{ij} = w_{ij} \cdot r_{ij}$$

Where:

- vij = The weighted normalized score

- *wij* = The weight of each criteria

The third step is to create the ideal and negative ideal solutions:

Ideal solution:

$$A* = \{v_1*, \ldots, v_n*\} \text{ where } v_j* = \{\max\ (v_{ij}) \text{ if } j \in J;\ \min v_{ij} \text{ if } j \in J'\}$$

Negative ideal solution:

$$A' = \{v'_1, \ldots, v'_n\} \text{ where } v'_j = \{\min\ (v_{ij}) \text{ if } j \in J;\ \max v_{ij} \text{ if } j \in J'\}$$

Where:

- J = The set of benefit criteria
- J' = The set of negative criteria

The fourth step is to create the separation measures for each alternative:

Separation from the ideal alternative:

$$S_i* = \sqrt{[\sum((v_j * - v_{ij})^2)]}$$

Separation from the negative ideal alternative:

$$S'_i = \sqrt{[\sum((v'_j - v_{ij})^2)]}$$

Where:

- S_i * = Closeness to the ideal solution
- S'_i = Closeness to the negative ideal solution

The fifth step is to create the relative closeness to the ideal solution:

$$C_i* = \frac{S'_i}{S_i * + S'_i}$$

The option which is closest to one will be the "best" according to the ideal solution, while the option closest to zero will be the worst.

Table 3 shows the top performing spare parts, as ranked using the TOPSIS approach. The ideal parameters in the TOPSIS calculation are as follows; demand is one unit, overhead cost is 520 DKK and lead time is 144 days. The data show that the top 99% or 7,811 spare parts from the data set are only 10.06 % from the ideal situation mentioned above. Table 3 shows that the number one ranked spare part is 2.8% from the ideal, while the number 100 ranking spare part is 5% from the ideal. Thus, there was very little difference between the top 100 ranked spare parts. This indicated that ranking all parts together resulted in little discrimination amongst them. Thus, there could be different clusters of parts in the data set and ranking them together may not help in distinguishing those most suitable. Hence, it was decided to cluster the dataset and then rank the clusters as well as spare parts within the clusters.

Table 3: Results from ranking all spare parts using TOPSIS

Material	Overhead Cost (DKK)	Lead Time (days)	Demand (12 months)	TOPSIS Score (Ci)	TOPSIS Ranking
56305665	364.74	85	1	0,972597613037653	**1**
53391A	311.50	99	1	0,971931770047372	**2**
56418987	321.29	68	6	0,96504184805561	**3**
56305436	428.82	50	1	0,964589392115614	**4**
8-51-05016	299.01	71	2	0,96433531665227	**5**
...	...	...	...	...	...
...	...	...	...	...	...
...	...	...	...	...	...
56304603	512,35	1	1	0,949103145137554	**100**

4..4 Solution refinement:

4.4.1 Cluster analysis to identify patterns amongst spare parts

Cluster analysis was conducted to understand how the spare parts were positioned according to the three criteria of: overhead cost (which includes inventory and transportation cost), lead time, and demand. K-means clustering is a method of effectively clustering complex data sets. The clustering algorithm was run by incrementally changing the number of clusters (k), until no centroid clusters changed positions. However, due to the complexity and size of the data set, no clear cluster was obtained using the k-means method. Due to the inconclusive k-means cluster analysis, Two Step Cluster Analysis (TSCA) with manual increase of cluster sizes was chosen. As stated by Mooi and Sarstedt (2011), TSCA is suitable "*if there are many observations in your dataset and the clustering variables are measured on different scale levels*". This is the case for the spare parts data set provided by the case company. Using this method, clusters of nodes were identified by first making a pre-clustering, and then using hierarchical methods. The method suits the data set well because TSCA can manage large data sets and allows for manual predetermination of the number of clusters. The cluster quality (silhouette measure of cohesion and separation) was calculated for each step as the number of clusters were incremented manually. The silhouette measure of cohesion (closeness) and separation (detachment) is a measure of the overall goodness-of-fit for the clustering solution (Mooi and Sarstedt, 2011). This measure is based on the average distances between the nodes and can vary between minus one and plus one. When using this measure, a silhouette measure of cohesion and separation below 0.20 is a poor solution quality, between 0.20 and 0.50 is a fair solution, and a measure above 0.50 indicates a good solution (Mooi and Sarstedt, 2011). The results of this analysis can be seen in figure 6.

As seen in figure 3, a solution with two clusters results in the best cluster quality - with a local spike in cluster quality at eight clusters. Increasing the number of clusters beyond eight results in a steady decrease in cluster quality. When investigating the composition and cluster sizes of the most optimum cluster (two) it can be seen that 92% of the nodes (7,254 spare parts) are in a single cluster. "Segments should exhibit high degrees of within-segment homogeneity and between-segment heterogeneity." and should be "familiar and relevant" (Mooi and Sarstedt, 2011). The solution of two clusters is therefore not considered adequate for further analysis, due to the significantly large cluster size and a low number of clusters. The spike at eight clusters was then investigated.

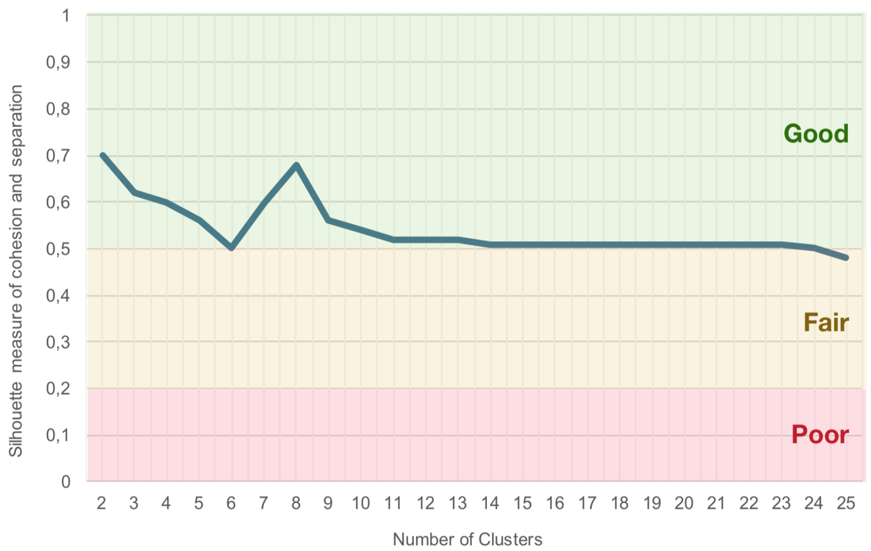

Figure 3: Cluster quality analysis - Silhouette measure of cohesion and separation

When using an eight cluster solution, the clusters featured a high level of within-segment homogeneity and between-segment heterogeneity. The spare parts were also more evenly distributed amongst the clusters as shown in Figure 4. The largest cluster (cluster 8) featured 2,470 spare parts (31.3% of the data set) and the smallest cluster consisted of 117 spare parts (1.5% of the data set) in Figure 4. The size distribution in the clusters was good, since no clusters featured the majority of the spare parts, while conducting the analysis with two clusters.

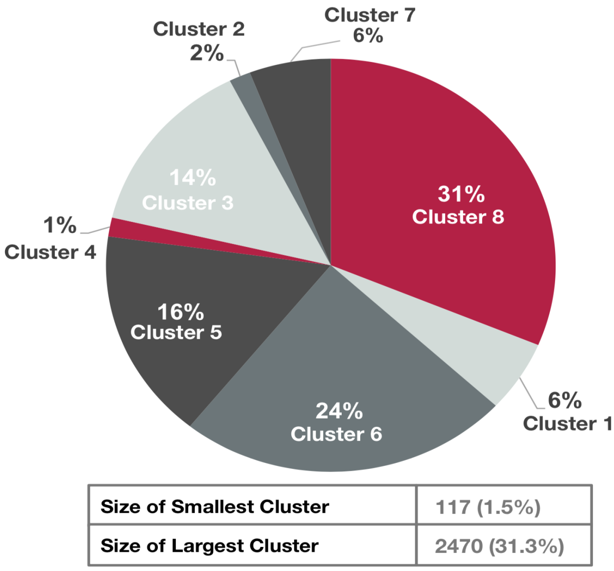

Figure 4: Cluster sizes for the eight-cluster solution

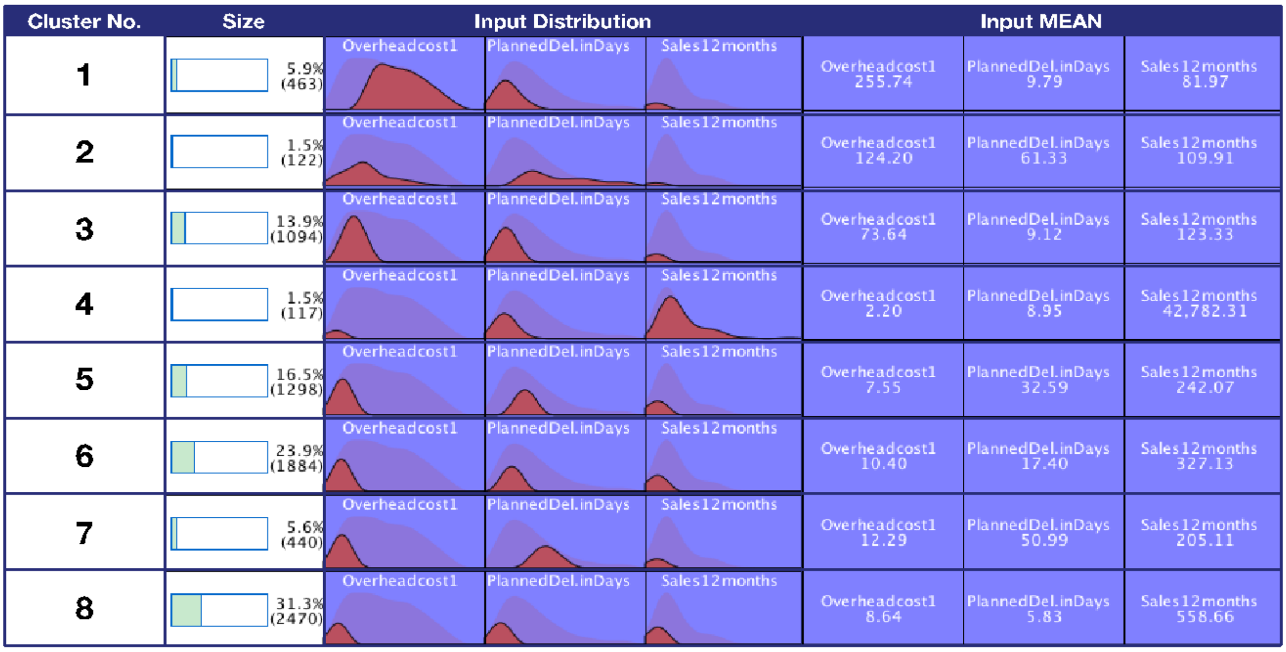

Figure 5: Cluster characteristics

The disadvantage of TSCA is that the results can depend on the order of data in the data set. To overcome this limitation, the data was randomized and tested an additional five times. The results from this analysis showed that every time the clustering algorithm was run, the cluster quality remained over 0.5. The average largest cluster size and average smallest cluster size was 33% and 1% respectively. Figure 5 shows the size (i.e., the number of parts), input distribution, and input mean of the different clusters.

The input mean shows the average input within each specific cluster. For example, when inspecting cluster eight, it can be seen that most of the input data are located in the leftmost portion of the overall data distribution, with an average overhead cost of 8.64 DKK, a lead time of 5.83 days and demand of 558.66 units per year. Using this data, it was possible to create a ranking of each cluster followed by ranking of the spare parts within each cluster.

4.4.2 Ranking of clusters and sample size determination for further analysis

As the case company was evaluating the feasibility of AM for spare parts production for the first time, they were interested in identifying *some* feasible spare parts and not *all* the spare parts, which could be produced by AM. Thus, it was decided to generate a sample of spare parts, which could then be evaluated further.

The selection of appropriate spare parts was completed through a three-step process:

1. Determination of spare part sample size by ranking of clusters
2. Ranking of the spare parts within the cluster
3. Manual inspection of technical drawings for selected spare parts

Having created the clusters, an assumption was made that some clusters can be potentially more suitable for AM than others. In order to find these clusters and to determine a sample within each cluster for further analysis, the clusters were ranked. For this analysis step, the two MCDM methods - AHP and TOPSIS - were used, with the previously mentioned weights of the factors to prioritize the clusters. The results of this ranking can be seen in table 4.

Table 4: Cluster rankings and sample size allocation across clusters using AHP and TOPSIS

	AHP		**TOPSIS**	
Cluster No.	**Rank**	**Sample size**	**Rank**	**Sample size**
1	1	29	2	17
2	2	24	1	18
3	3	16	4	14
4	8	2	8	1
5	5	10	5	14
6	6	7	6	13
7	4	13	3	14
8	7	4	7	12

As can be seen in table 4, clusters are ranked very similar to using AHP and TOPSIS. The difference between the two approaches lies within the first four cluster rankings, where cluster one and two appeared to have switched places, as well as three and seven. Since the difference between the two methods was not significant, and there was no tangible advantage in understanding deviation from the ideal cluster, AHP was the method used to rank the clusters. The proportional allocation from the AHP score determines the sample size from each cluster. In table 3, a sample size of 100 was distributed amongst the clusters based on the AHP scores of the clusters. Following the ranking of clusters and determination of sample sizes within each cluster, the selected spare parts within each cluster were analyzed to identify those most suitable.

4..4.3 Ranking of spare parts within clusters using TOPSIS

Spare parts within each cluster were ranked to choose the most eligible spare parts, which were suitable for AM. TOPSIS was deemed to be the most suitable, as the method compares each spare part to the ideal and negative ideals, within each cluster. In table 6, the positive and negative ideals for each of the eight clusters are depicted. After calculating the positive and negative ideals, the spare parts were scored based on the distance from the ideal solutions and the weights of the parameters. Combining this ranking with the sample size gives a list of the most eligible spare parts within each cluster.

Table 5: Results from weight changes in cluster 1 & 2

Cluster 1 Weight Change Results						
	Lead Time		Overhead Cost		Demand	
Weight change	Sample change	Sample change %	Sample change	Sample change %	Sample change	Sample change %
+2%	-1	-3%	0	0%	0	0%
+5%	-2	-7%	2	7%	0	0%
+10%	-4	-14%	3	10%	0	0%
-2%	0	0%	-1	-3%	0	0%
-5%	1	3%	-2	-7%	0	0%
-10%	3	10%	-4	-14%	0	0%
Cluster 2 Weight Change Results						
	Lead Time		**Overhead Cost**		**Demand**	
Weight change	Sample change	Sample change %	Sample change	Sample change %	Sample change	Sample change %
+2%	1	4%	0	0%	0	0%
+5%	1	4%	0	0%	0	0%
+10%	1	4%	0	0%	0	0%
-2%	0	0%	0	0%	1	4%
-5%	0	0%	0	0%	1	4%
-10%	0	0%	0	0%	1	4%

Table 6: TOPSIS positive and negative ideal within each cluster

Cluster No.	Input	TOPSIS Ideal (+/-)	
		Positive Ideal (+)	Negative Ideal (-)
1	LT	999.11 days	129.75 days
	D	6 units	982 units
	O	519.63 DKK	140.68 DKK
2	LT	907.29 days	0.07 days
	D	11 units	980 units
	O	428.82 DKK	0.00 DKK
3	LT	25.00 days	1.00 day
	D	1 unit	6,250 units
	O	141.65 DKK	30.59 DKK
4	LT	36.83 days	1.76 days
	D	12,142 units	28,6365 units
	O	48.81 DKK	0.00 DKK
5	LT	41.00 days	25.50 days
	D	1 unit	11,901 units
	O	89.11 DKK	0.00 DKK
6	LT	25.60 days	12.00 days
	D	1 units	12,092 units
	O	71.22 DKK	0.00 DKK
7	LT	78.00 days	42.00 days
	D	1 units	17,318 units
	O	79.76 DKK	0.00 DKK
8	LT	12.86 days	1.00 day
	D	1 unit	11,992 units
	O	39.13 DKK	0.00 DKK

LT: Lead time D: Demand O: Overhead Cost

4.4.4 Sensitivity analysis of ranking of spare parts within clusters by TOPSIS

In order to investigate the robustness of the TOPSIS method, which was used to rank the spare parts within clusters, sensitivity analysis was conducted. The analysis showed that changing the weight of the parameters affected the sample sizes for each cluster. In table 6, the two most affected clusters, 1 and 2, are shown. The column "Parts removed" shows the number of parts from the specific cluster that were removed as a consequence of change of weight of factors. For example, by changing the weight of the lead time by +5% the sample size for cluster 1 decreased from 29 to 28. The "Parts removed %" showed the percentage of the parts removed from the cluster compared to the original allocation. In table 7, weight changes and effects for clusters 1 and 2 can be seen.

For example, for cluster 1, reduction in weight of lead time by 10% removed 14 parts equivalent to 48% of the parts from the original sample, while increasing the weight of overhead cost by 10%, removed nine parts, which is equivalent to 31% of the sample that were removed from the original sample. Thus, for cluster 1, a reduction in weight for lead time and an increase in weight for overhead cost will induce the largest change in the cluster composition. For cluster 2, it can be observed that increasing the weight of lead time by 5% removes only one part from the original sample but increasing it by an additional 5% to a total of 10% will move 10 parts. Decreasing the weight of overhead cost by 10% has the effect of removing 67% of the parts from the original sample size allocation. Hence, cluster 2 is more sensitive to overhead cost. Thus, from the sensitivity analyses, we can conclude that demand had little to no impact on cluster composition. Nonetheless, cluster composition, and hence final selection of spare parts for AM, will change if the weights of lead time and overhead costs are changed significantly.

Table 7: Results from weight changes in cluster 1 & 2

Cluster 1 Weight Change Effect on Spare Parts in Sample						
	Lead Time		Overhead Cost		Demand	
Weight change	Parts removed	Parts removed %	Parts removed	Parts removed %	Parts removed	Parts removed %
+2%	1	3%	0	0%	0	0%
+5%	1	3%	3	10%	0	0%
+10%	3	10%	9	31%	0	0%
-2%	0	0%	1	3%	0	0%
-5%	5	17%	2	7%	0	0%
-10%	14	48%	3	10%	0	0%
Cluster 2 Weight Change Effect on Spare Parts in Sample						
	Lead Time		**Overhead Cost**		**Demand**	
Weight change	Parts removed	Parts removed %	Parts removed	Parts removed %	Parts removed	Parts removed %
+2%	0	0%	1	4%	0	0%
+5%	1	4%	1	4%	0	0%
+10%	10	42%	2	8%	0	0%
-2%	1	4%	0	0%	0	0%
-5%	1	4%	3	12%	0	0%
-10%	3	12%	16	67%	0	0%

4.4.5 Final selection of spare parts through technical evaluation of drawings and expert validation

The technical drawings for all 100 selected spare parts were requested from the case company; however, only a total of 54 technical drawings could be obtained. This was because some of the drawings were not provided by the third party suppliers to the case company or because for older spare parts, technical drawings were not created or documented. The files provided included CAD drawings and technical specification sheets in PDF format.

Using the 2D or 3D drawings, the material and tolerances were inspected to determine if the product was eligible for AM. This step should have been completed during the technological attribute screening; however, it was postponed due to lack of data. After this step, 45 spare parts were discarded. The reason for this was that the spare parts included complex subassemblies, had high tolerance requirements or featured electronic components or other unprintable materials as determined by examining the printer database. Complex assemblies were not considered in this research. However, assemblies featuring simple components were included and separated into subcomponents. An example of an assembly deemed suitable for AM is shown in Figure 6.

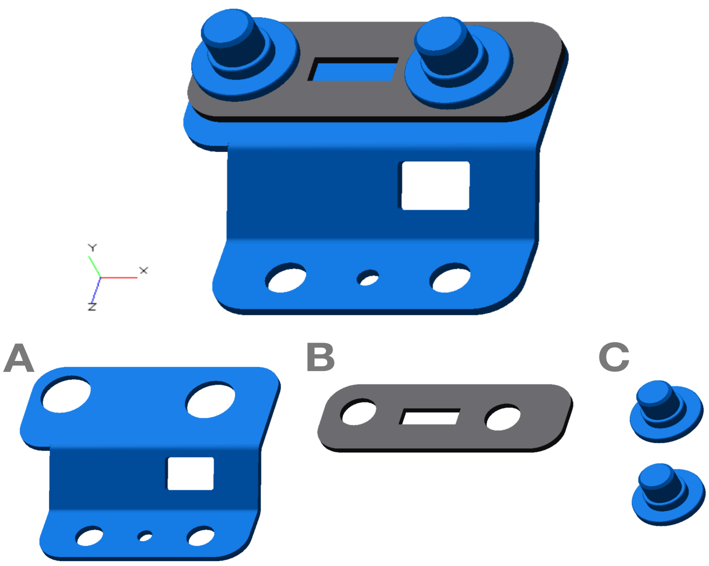

Figure 6: Typical subassembly considered in the study

By going through the data set, it was not always possible to identify assemblies without looking at individual drawings. Furthermore, digital drawings were not available for all the requested parts and, hence, were not accessible to the research team. Hence, from this analysis, nine spare parts were chosen to be suitable for AM. The results of the spare part selection exercise were presented to three managers from the spare parts and procurement functions. The managers validated these findings and agreed that the nine selected parts could be taken up for a detailed business case development in favor of using AM.

5.0 Discussion

Developing a methodology for selecting spare parts that are suitable for AM for the case company highlighted multiple challenges associated with data collection and evaluation. The outcome of using our proposed approach shows that the choice of the specific method and the process followed will depend on the number of factors used for assessment, the relationship between the factors, the number of parts to be evaluated, the specific characteristics of the dataset and data availability as well as the extent of discrimination amongst parts, which can be obtained by using the method.

Our results show that for a company with a large portfolio of spare parts with very different characteristics, trying to rank the parts will not help in distinguishing the parts suitably from the point of view of suitability for AM. Conducting cluster analysis will help in understanding the part characteristics better, the clusters and parts within the clusters can then be ranked.

5.1 Generalizability of the proposed methodology

Following the substantive theory development phase of design science research, we discuss the generalizability of the proposed approach. The proposed approach is particularly suitable where a scoring method to rank all parts in a spare parts portfolio fails to achieve sufficient discrimination. The suitability of the proposed approach is not simply restricted to a part selection problem for AM but can be used for other applications such as suitable materials and process selection for AM where materials characteristics and AM technology characteristics need to be matched with parts characteristics and requirements. Understanding parts characteristics, grouping similar parts together and identifying which are suitable for which type of materials and which specific AM technology can also be attempted using our proposed approach. The approach also underscores the importance of using both the data-driven and expert driven approach to address the problem, which should also be used to solve similar problems in the industry.

5.2 Development of a generalized framework for spare parts selection for AM

It is important to take a pragmatic approach while conducting such an exercise by taking into account the company's specific needs. For example, the expert-driven bottom-up approach as demonstrated in Lindemann et al. (2015) is useful, especially in contexts where sufficient data are not available. Thus, there is a need to develop a systematic process for conducting the parts selection exercise, considering the context of the company and the availability of data.

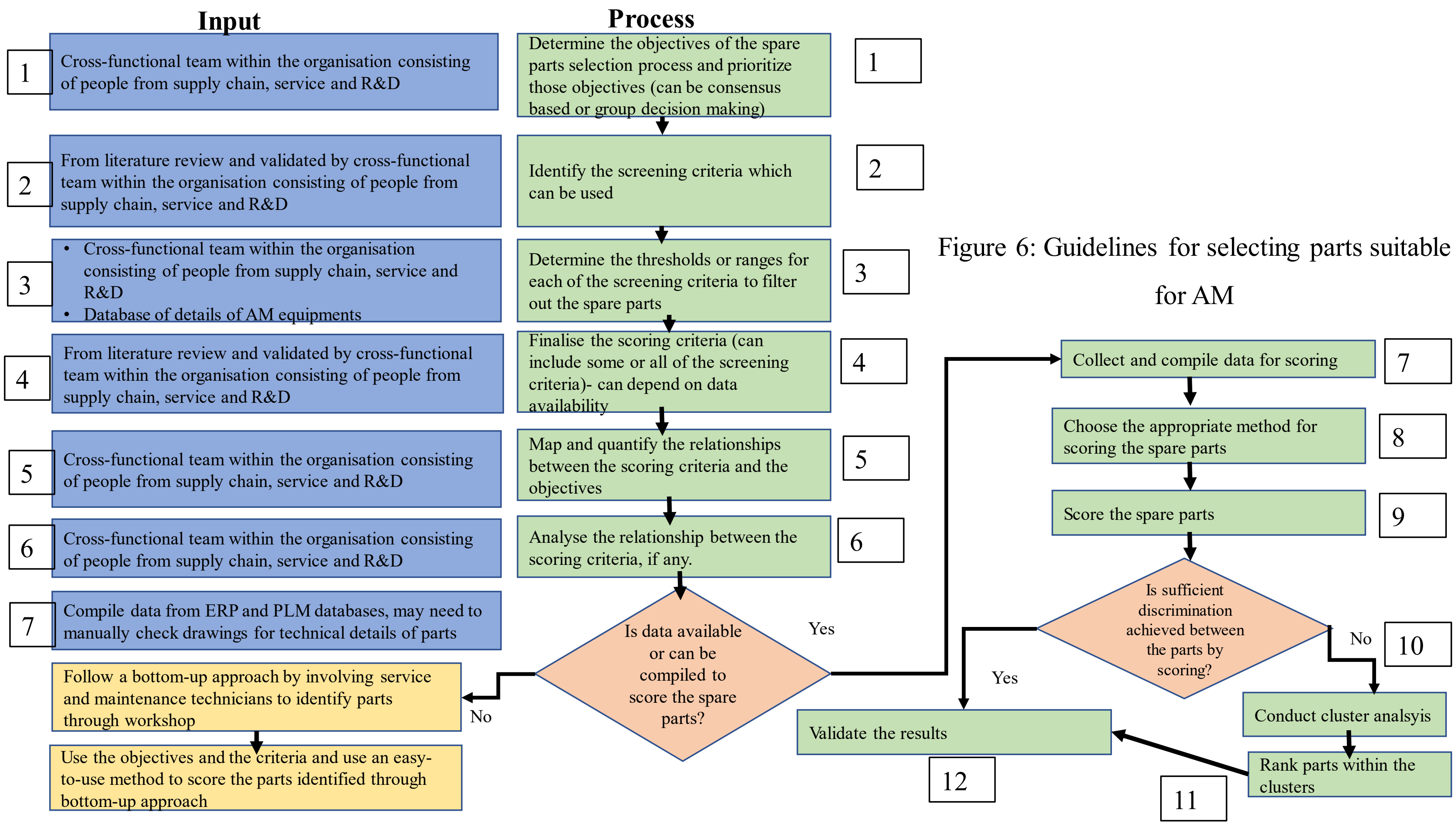

Figure 7: Guidelines for selecting parts suitable for AM

We outline this systematic process in Figure 7, which can serve as a guideline for companies trying to assess whether their spare parts portfolio is suitable for AM. This process includes specifying the objectives, identifying the screening criteria and their thresholds, finalizing the scoring criteria, understanding the relationship between the scoring criteria and the objectives and, finally, collecting the necessary data before scoring the parts. To conduct the above exercise, a cross-functional team consisting of people from the supply chain, service and R&D needs to be involved. The team needs to specify the company specific objectives, finalize the screening criteria, determine their thresholds and ensure that data are made available for validation of the findings. If it is not possible to collect data for all parts due to lack of data availability of the data in the digital form, the companies should follow a bottom-up approach to identify spare parts that are suitable for AM by holding workshops that involve the maintenance and service technicians. The content of these workshops should include an overview of the potential for AM, and identify specific questions regarding which spare parts create problems for maintenance and service due to lack of availability and due to sheer complexity. If several potential spare parts are identified through these workshops, the identified scoring criteria can be used to score the spare parts based on expert judgment. If only a few spare parts are identified, companies can identify the appropriate AM technology and equipment and then develop a business case by relying on total cost of ownership models.

6.0 Conclusion, limitations and opportunities for future research

This paper focused on identifying the most suitable spare parts to be produced using AM. TOPSIS, MCDM approach, and cluster analysis were used to identify suitable spare parts. Sensitivity analyses were conducted to check the robustness of the results. The identified parts were validated using experts from within the case company.

The contributions of this paper are two-fold. First, we have developed a comprehensive data-driven approach, which combines expert knowledge with available data of the spare parts. The proposed approach is particularly suitable where an attempt to rank all parts in a spare parts portfolio fails to achieve sufficient discrimination. Second, we have followed a systematic design science approach with a focus on developing an 'artifact', i.e., a step-by-step process to address the parts selection problem for AM and also comment on the generalizability of the approach beyond the application context in the case company.

The research has certain limitations. Due to data limitations, it was not possible to screen the initial population of spare parts based on materials, weight, and tolerances. Some simplifying assumptions were made regarding the exclusion of parts with more than 100% of overhead costs and exclusion of high value items, which were assumed to be primarily electronics. These assumptions were made while focusing on the current situation in the company, leading to the exclusion of parts which may have high inventory and, hence, do not need to be produced using AM in the current situation or in situations where there is no willingness to print electronics items to start with. Ideally, such screening would reduce the number of feasible spare parts significantly, which can then be thoroughly assessed. Also, the selection of spare parts using the above process was not exhaustive but, instead, a sample of 100 parts was selected, out of which only 54 parts could be evaluated. Thus, the company can potentially evaluate many other parts. As companies identify more spare parts, which can be manufactured using AM, the analysis of characteristics of those parts and identifying patterns using different machine learning techniques can ensure that the entire spare parts selection process for AM need not be repeated when new products are developed, and when new parts are added to the spare parts population. In survey research, it is a common practice to check for missing data and use suitable imputation techniques (Tsikriktsis, 2005). Future research should also explore the best approaches to check for data quality, missing data, and impute those using the most suitable approach in the context of the parts selection problem for AM.

Currently, no clear guidelines are available in the literature in terms of choosing the appropriate methodology for such parts selection problems. Future research should be directed towards developing guidelines concerning the choice of the most appropriate method depending on the context. Thus, there is a need to compare the results following different MCDM methods and further validating them. Once spare part selection has been conducted, the most suitable spare parts can be profiled, so that the parts selection process can be automated following machine learning approach. Such an approach is applied by commercial service providers who provide part identification as a service. Nevertheless, such an approach is not suitable for AM adopting company as they may not have referenced parts. Such companies can buy the services from an AM software service provider; however, several companies we interacted would like to try independent approach customized for their portfolio as demonstrated in this paper.

For the selected spare parts, the most suitable AM technology and equipment have to be assessed primarily based on build volume, materials which can be processed, surface finish, and tolerances which can be achieved, including post-processing requirements. In future, with available data, such technical feasibility should be considered as part of the selection process rather than after selecting the parts.

The outlined process also assumes no change in the design of the parts. For spare parts which are not the most suitable for AM using existing designs, the need for additional design changes has to be explored by considering a change of materials or optimal geometries. There is a need for developing an integrated decision support system for parts selection, AM technology and equipment selection and assessment of design change alternatives. These issues can be explored in future research.

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