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Additive Manufacturing Decision Support Systems: A Systematic Literature Review Discerning Current and Future Directions

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Abstract. Additive manufacturing (AM) was introduced the 1980's for rapid prototyping (RP) purposes but now AM provides complementary techniques to conventional manufacturing processes and offers advantages when components can be exacting, impossible, and too costly to be produced by conventional methods due to complex structures and geometric configurations, which require tailored designs. They are also often mass-customized components, with custom-made properties and low volume production requirements making AM the *'technology of choice'* since its added-value aspects cannot be achieved by any other manufacturing technologies. These advancements in manufacturing, demand standardized fact-based decision support systems (DSSs), to support AM practitioners in their task selecting the most suitable techniques for given applications. Hence, this paper aims to increase the understanding of what - of how - DSSs are used in selecting and utilizing AM in various applications. This paper's core message, considering practical implications, is to guide and support AM researchers with an overview of the DSSs for AM landscape. This paper presents and compares different models and tools classified within four categories used as DSS for AM and identifies their advantages and disadvantages by conducting a 3-step systematic literature review (SLR). A total of 388 literatures were initially retrieved, and according to an inclusion criteria analysis, the literatures were evaluated. This is the first SLR emphasizing and synthesizing obtainable literatures on AM DSS. Until now, this topic has acquired narrow exploration; however, the authors believe it is of rapidly growing importance to both scientists and practitioners.

Keywords. Additive Manufacturing (AM); 3D Printing (3DP); Decision Support System (DSS); Decision-Making Tools; Systematic Literature Review (SLR).

1. Introduction and Motivation

Additive manufacturing (AM) is one of the advanced manufacturing techniques that gave a breakthrough in how companies design, prototype, and manufacture products. AM has various advantages as it enables development of intricate geometrical components for

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medium/low volume production [1]. AM produce objects layer by layer from a CAD design. [2]. AM technologies have been initially utilized in the early 80s for rapid prototyping (RP), however, over the last 10-15 years the potential for production of end-use parts has been explored predominantly in the metal AM industry [3]. A big opportunity for manufacturing companies is to produce parts in smaller quantities while not sacrificing cost-effectiveness due to the technological advancements in the AM industry e.g., new processes and materials. Hence, many companies e.g., in aerospace, automotive, medical/dental device, and health care industries are adopting and implementing AM [1].

AM also has some limitations and thus it might not be suitable for the production of certain parts in comparison to conventional manufacturing techniques e.g., machining [4]. For example, in the mass production of simple parts that are 2 or 2.5 dimensional and/or have no re-entrant features. Another limitation, which is of more interest to this research, is having access to a robust fact-based decision support system (DSS) for selection of the most suitable production process. Considering aspects e.g., accuracy and tolerances, surface finish, cycle, and setup times, cost, and material properties. Putting aside AM technological and material developments, which are continuously of focus in research, to maximize the AM processes capabilities, generic modular DSSs must be designed and applied to assist with the most suitable process selection to obtain the best outcomes e.g., in terms of performance mechanical properties. This paper conducts a systematic literature review (SLR) on AM DSS to review the prior studies of AM decision support system (AM DSS) aiming to identify the outcomes of these studies e.g., consensus, disagreement, practicalities, and shortcomings. The purpose is to analyse the existing DSSs utilized for the selection of AM manufacturing techniques considering various aspects e.g., cost, material, surface finish, mechanical strength, ease of manufacturing, size, time, quantity, geometric complexity, sustainability. Hence, this paper answers the following research questions (RQ): *What are the DSS which have been developed or used for AM? How can DSS enable users to select the right AM processes?*

2. Systematic Literature Review

Systematic literature review (SLR) is *"a specific methodology of research, developed to gather and evaluate the available evidences pertaining to a focused topic"* [5].

Figure 1. *Steps in a systematic literature review also followed in this study* [6]

Figure 1 shows the steps in an SLR process which were taken during this research. The search engines used in this SLR are Web of Science, ScienceDirect, and SCOPUS. Figure 2 shows this study's search procedure. The retrieved literature was forward traced and backtracked for literature that is relevant. Journal articles and peer-reviewed scientific conference papers were selected for this SLR. The protocol includes a 'studies selection' section, where inclusion and exclusion criteria are decided upon. The inclusion and exclusion criteria of this SLR were: **1)** literature must contain information regarding DSS in AM and must provide information on how to implement DSS for process selection, and **2)** it should give information on how decisions would be affected for applications of AM e.g., finishes, accuracy, and manufacturing cost for process selection.

Figure 2. *Systematic Search procedure also followed in this study* [6]

The literature retrieved using various search string keywords was documented in a database using reference management software, and they then went through a 'title screening' process. Followed by 'abstract screening', 'introduction & conclusion screening' processes, and detailed analysis of the selected literature. Literature was screened based on the protocol and any doubt of inclusion was further examined [7]. The list of excluded papers was also documented for records and cross-checking. To assess the quality of the literature after the inclusion processes, a deeper assessment of the full text was performed. The quality was assessed by various discussions with the co-authors hence the facts given in the report are reasonable and defendable [7]. Figure 3 and table 1 below illustrate respectively the SLR processes, and the search engines, and the search string keywords used in this SLR.

Table 1. *Search engines and search strings keywords for this SLR*

Search No.	Search Engine	Search String Keywords
1	WOS	TI= (("ADDITIVE MANUFACTURING") OR (" 3D PRINTING") OR ("RAPID PROTOTYPING")) AND TI= (("DECISION SUPPORT SYSTEM") OR ("DSS") OR ("DECISION MAKING TOOL"))
2	WOS	TI= (("ADDITIVE MANUFACTURING") OR ("RAPID PROTOTYPING") OR ("LAYER BY LAYER")) AND TS= (("DECISION MAKING") OR ("DECISION SUPPORT") OR ("GUIDANCE SYSTEM")) AND AB=(("COST") OR ("MATERIAL") OR ("DESIGN") OR ("FINISH") OR ("QUALITY") OR ("STRENGTH"))
3	WOS	AK=(("AM") OR ("Rapid prototyping") OR ("3D printing") OR ("Layer by layer manufacturing")) AND TI= (("Cost optimization") OR ("Material selection") OR ("Process selection") OR ("Selection Process") OR ("Decision making"))
4	ScienceDirect	("Additive manufacturing" OR "3D printing" OR "3D fabrication" OR "layer by layer manufacturing" OR "rapid prototyping") AND ("Decision support" OR "Decision support system" OR "Decision making" OR "guidance system")
5	ScienceDirect	("Additive manufacturing" OR "3D printing" OR "layer by layer manufacturing" OR "rapid prototyping") AND ("Decision support system" OR "Decision making") AND ("Cost optimization" OR "material selection" OR "Process selection")
6	SCOPUS	TITLE-ABS ("AM" OR "layer by layer manufacturing" OR "3D printing" OR "freeform fabrication" OR "rapid prototyping" OR "3D fabrication") AND TITLE-ABS ("decision support system" OR "decision guidance" OR "decision support model" OR "decision tree" OR "shared decision making") AND (LIMIT-TO (SUBJAREA, "ENGI")) AND (LIMIT-TO (LANGUAGE "English"))
7	SCOPUS	TITLE-ABS ("AM" OR "layer by layer manufacturing" OR "3D printing" OR "layer by layer manufacturing" OR "freeform fabrication" OR "rapid prototyping" OR "3D fabrication") AND TITLE-ABS ("decision support system" OR "decision guidance" OR "decision support model" OR "decision tree" OR "shared decision making") AND (cost OR material OR size OR quality OR "surface finish") AND (LIMIT-TO (SUBJAREA, "ENGI"))
8	SCOPUS	TITLE ("AM" OR "layer by layer manufacturing" OR "3D printing" OR "freeform fabrication" OR "rapid prototyping") AND TITLE ("decision support system" OR "decision guidance" OR "decision support model" OR "decision tree" OR "shared decision making") AND (cost OR size OR quality OR "surface finish") AND (LIMIT-TO (SUBJAREA, "ENGI"))
9	SCOPUS	TITLE-ABS-KEY ("AM" OR "3D printing" OR "freeform fabrication" OR "rapid prototyping") AND TITLE-ABS-KEY ("decision support system" OR "decision guidance" OR "decision support model" OR "decision tree" OR "shared decision making") AND (cost OR size OR quality OR "surface finish") AND (LIMIT-TO (SUBJAREA, "ENGI"))

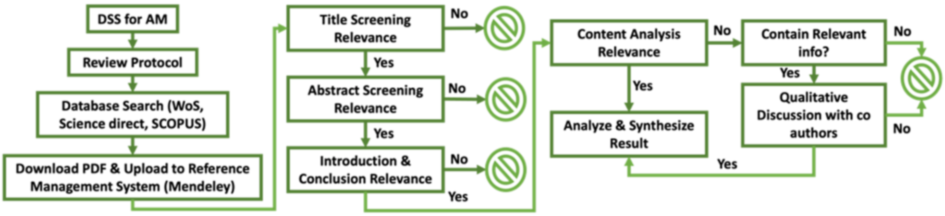


Figure 3. *Steps taken in this systematic literature review*

3. Results

The search string keywords, seen in table 1, gave 388 papers, and after 'title screening', 137 papers were selected. The papers were then assessed for duplication in different search strings and engines, giving 74 papers. After the duplicated papers were removed, the remaining 74 papers were screened by their abstracts, and any papers in doubt were considered for further screening. After the introduction and conclusion screening, 40 papers [1-4] [8-43] were found following the SLR protocol's inclusion criteria, which represents 10.3% of the original literature search. Figure 4 summarizes the process. These 40 selected literatures (29 journal articles and 11 conference papers) were then read fully and analytically interpreted for deeper evaluation. Important parameters established in the literature are recorded and compared for an understanding of the research topic trends e.g., the literature was published in a period from 1997 to 2020.

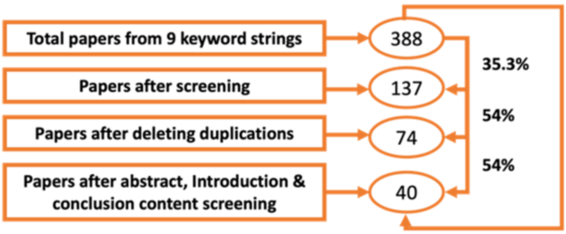
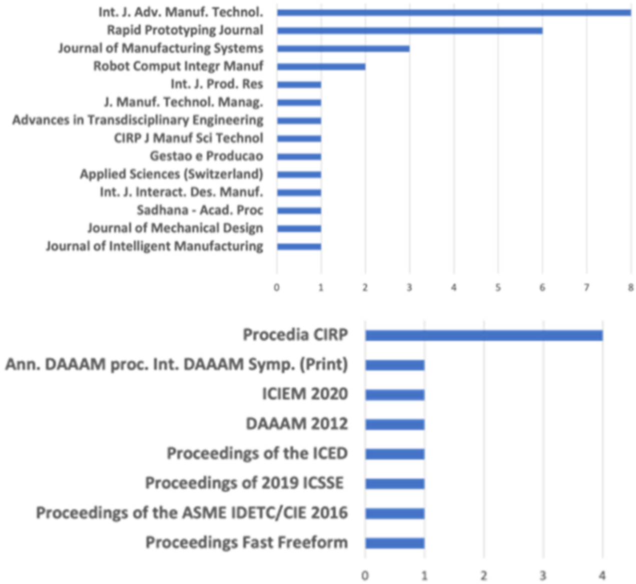


Figure 4. Inclusion criteria analysis in this study

Figures 5 & 6 shows the quantity of literature across journals and conferences proceedings. There are different methodologies and decision-making techniques, which were applied as DSS for AM processes selection in the studied literature. These are mapped in figure 7. Sometimes, similar techniques or methodology is used, but have been utilized differently. The classification in figure 7 breaks down the topics into subdivisions to understand them better. It also facilitates identifying and understanding the similarities and differences of the processes compared in the next section, discussion.

The main DSSs reported in the selected literature are in four categories: *multi-criteria decision making (MCDM)*, *mathematical modeling*, *software-based,* and *design approach*. DSSs are subdivided into categories because of the following reasons: **1)** *MCDM* methods follow a ranking process and decision matrix to perform the decision support, **2)** *Mathematical modeling* performs mathematical calculations with cost, build time, material consumption, etc., and decisions are based on the results, **3)** *Design approach* uses design and checks for various complications to select the best method, and **4)** *Software-based* uses historical data to program the decision-making process.



Figures 5 & 6. Distribution of the selected articles in Journals & selected papers in conference proceedings

MCDM is the most commonly used technique with 52% of the selected literature reported. The second, DSS, is a *software-based* technique, followed closely by the *design approach* having a 13% share and *mathematical modeling*, 10%. There are also 5% of the selected literature, which cannot be included in any of the above 4 categories. This "other" category has low significance in terms of process selection; The studies gave a basic selection process explained via general aspects e.g., usage of excel sheets.

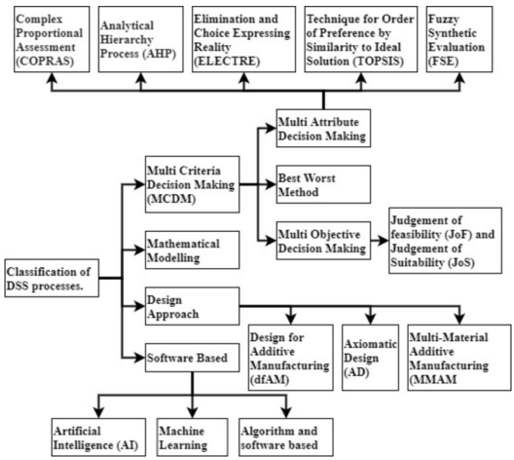


Figure 7. Classification of DSS processes in the studied literature

The selected literature's analysis suggests that DSSs have been utilized for different applications in various sectors as classified in figure 8. An exceptional application, 'austere environment' was the most unique application, where the key point of utilizing a DSS was to make a quick decision in product manufacturing. The manufactured products are used in various combat zone equipment whereby the capacity to make a fast decision for AM process selection enabled production of the part with a short lead time.

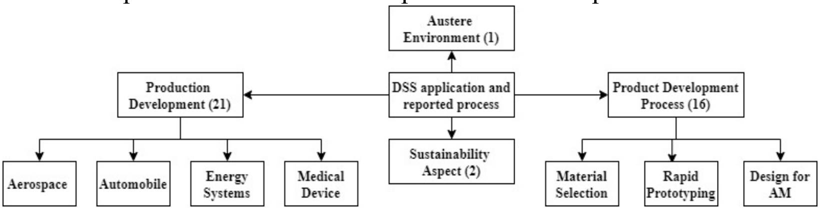


Figure 8. DSS applications in the selected literature and the number of papers/articles for each category

4. Discussion

This section presents a comparison of different DSS methodologies based on the SLR results. Each DSS methodology is also briefly described including its the pros and cons.

***M**ulti-**c**riteria **d**ecision-**m**aking (MCDM)* is further classified into different processes. MCDM strategies are designed for decision-makers to provide them with the best alternatives from a finite range of options. The methods used are divided into two steps: the *screening method* and the *ranking method*. When we compared the ***A**nalytic **H**ierarchy **P**rocess (AHP)* utilized in the selected literature, we saw some common structures in the methodologies. A process is broken down into different hierarchy levels for understanding and assessment of the problems. This enables the user to systematically analyze AM processes by comparing two criteria at a time and to determine its weighed criteria. This comparison is important as it forms the basis of the process giving results in the form of a ranking between AM processes. Using AHP, the cost can be calculated, and the best suitable materials can be selected using a decision matrix. Since AHP only conducts par-to-par comparisons, it is difficult to evaluate all competitive parameters at the same time as it takes more time and effort. Most of the AHP processes, used in the selected literature, have almost the same working procedure.

While using the ***T**echnique for **O**rder **P**reference by **S**imilarity to an **I**deal **S**olution (TOPSIS)* process, the methodology followed is like the AHP process. Modified TOPSIS determines the ranks between RP process by pair-wise comparison and then provides the final rankings. Using the Optional Navigation Module, the users can form preferences and multi-dimensional data visualization (MDDV) tool to visualize their chosen criteria. Once the boundary for these parameters is set, changing the boundary influences the final score. For each attribute, the user should look at the performance distribution of these choices to see what levels of performance are possible. The major difference between AHP and TOPSIS is that the user can specify the requirements and has the option to filter out the non-feasible alternatives. This process gives the decision-makers the freedom to eliminate the entire process types from the outset of the down-select process.

***CO**mplex **PR**oportional **AS**sessment (COPRAS)* method can manage qualitative attribute data. The methodology applies to any decision-making situation and provides more effective results in comparison to TOPSIS and AHP. It has a simple flow of analysis as the input for AHP and TOPSIS depends on the user and if the user changes the relative importance of the considered criteria, then their ranking will be different from the actual one. The ranking obtained from using this method is more reliable than the other previous methods. In the literature where the COPRAS method is used to make the final calculation, AHP can be used to find the weights of the relative importance of attributes, or the user can assign weights to the criteria on their preference [8].

***F**uzzy **S**ynthetic **E**valuation (FSE)* is a web based DSS process, which is divided into different hierarchy levels. This process also uses one of the ranking methods to rank different RP processes. E.g., when it comes to lesser environmental impact, the fuzzy ANP-TOPSIS method is suitable. AHP-conjoint analysis provides better results when they are combined. The downside of each process outweighs and compensates for the disadvantages of the other processes.

All the DSSs used, require selecting an RP process, where applied ranking methods e.g., AHP, TOPSIS, Best Worst Method (BWM) are used to rank the processes. Users consider the BWM technique to be better than AHP since it has better ordinal consistency, consistent comparison, minimum total deviation, closer weight ratio, and fewer comparisons. Software's based processes like machine learning (ML) and artificial intelligence (AI) are also being used in DSS [2]. When it comes to AI-based software, different tools e.g., SIEMENS NX are used to extract and store data. Konstanz Information Miner (KNIME) is another open-source tool, which creates a workflow in the data processing and maps the complete process from data selection to evaluation, interpretation, and visualization. The KNIME is used for data processing when AI is used.

In one of the literature [9] a cloud-based ML tool has been implemented. A set of criteria was built, using both traditional manufacturing and AM literature, and was tested to understand if they meet the requirements of a quick screening tool [9]. A database of parts and assemblies needs to be developed and each needs to be assessed for AM potential. Afterward, when a new part or assembly needs to be assessed for AM candidacy, the same selection criteria will be extracted from it and will be fed to the decision model. The decision model will then use the labeled database of historical data to form the final AM candidacy decision. There is an agent-based DSS where machine agents are used to communicate with specific computer-aided manufacturing (CAM) systems that correspond to each 3D printer they represent. These CAM systems are typically associated with a few process profiles that contain special parameters values for different combinations. CAM software utilizes the latest firmware update so that the most updated information is provided. An agent with operators and other information technology (IT) systems could also be done independently. When it comes to software processes, different approaches are being used. Each of them is different from the other.

In mathematical modeling, see table 2, different models are proposed to establish economic models. Parameters, considered in these models are different from each other with some similarities. Selected models are more detailed and well explained with examples where they consider models based on energy per part manufactured and cost factors [10]. Models used in a few pieces of literature are much simpler, and not well explained [11]. Selected cost models are focused on four different RP properties of building accuracy, surface roughness, building time, and building cost [12].

In the design approach, the axiomatic design method is ideal for developing new product designs and assessing designs at early stages in the process. The axiomatic design considers the manufacturing of the component after the design has been defined in the physical domain, and the process variables describes the process domain.

Table 2. Mathematical model approaches [10] [11] [12]

Literatures	Models used
Toward Generic Models for Comparative Evaluation and Process Selection in Rapid Prototyping and Manufacturing.	Cost models for • Material cost • Machine running cost. • Cost in data preparation • Cost in post-processing.
A comparative assessment of energy demand and life cycle costs for additive- and subtractive-based manufacturing approaches	Models proposed for each energy per part manufactured and cost. • Quantifies the cumulative energy demand per produced part. • Quantifies the total cost per produced part.
Framework to combine technical, economic, and environmental points of view of additive manufacturing processes.	Models presented are: • Electrical model • Fluid model • Material consumption model • Economic model • Technical model

In Decision Support System for Additive Manufacturing (DS-SAM) the critical required parameters, are the inputs to the system. Then the design rules are set and act as guidelines for the new ideas and concepts. Then, the binary evaluation determines the efficacy for each of the ideas. Finally, cost assessment and design verification are performed. In DfAM, complex geometries for optimized performance are designed. Based on aesthetical needs of the product, the process can be selected. But, in multi-material additive manufacturing (MMAM), the process is checked against DfAM rules to ensure manufacturability. To select a suitable MMAM process, the parameters should match the database, which is already organized via technical specification. Designers need to select portions from the database specifications, giving a limited choice for the designer. The database needs frequent updating. There are no such similarities with the methods used in the design approach for DSS. Each process has its method of getting the best results.

Table 3. AHP in product development applications [34] [41] [43]

Literature	Unique features for implementation in product development in terms of AHP
AM process selection based on parts selection criteria	Uses constraining factors like the build dimensions, mechanical properties, etc., for the process of ranking which helps in the comparison.
Applying decision methods to select rapid prototyping technologies	Two scenarios are considered for the process of ranking: • The cost of part (C) and build time (B) was considered the most important factors followed by elongation, tensile strength, accuracy, and surface roughness. • Where accuracy (A) and surface roughness (S) were considered most important followed by elongation, tensile strength, cost of the part, and build time. To evaluate the approach, a comparison matrix for the criteria was created.
Material selection methodology for additive manufacturing applications	For performance, physical, and thermal requirements, three criteria were identified as governing criteria for the screening stage, namely: material hardness, surface finish, and melting point.

When we performed an in-depth investigation into the different AM processes used in various applications, we noted that in product development (PD), a variety of DSSs was used e.g., software-based process, machine learning, and various MCDM processes e.g., BWM, TOPSIS, AHP, etc. This might indicate how important, AM has become in PD. This analysis helps us to understand the scope of DSS in terms of PD, which has been increasing, and that may justify more literature availability. Another finding is that

AHP is one of the DSS techniques, which is mostly used in the PD domain. When we investigated what type of products and processes AHP was applied to; we found out that when a new product is being developed, usage of AHP could be crucial as a DSS for process selection, and for identifying and selecting the product's features. AHP is a technique, which ranks specific features in terms of usability, cost, technical features. and helps in selecting the process to prototype the product and can also aid in understanding the functions of the products being developed. Table 3 provides information regarding certain unique methods in the selected literature for the process of AHP. These features are implemented based on the type of product that is produced.

Here the uniqueness is the few factors that are considered for the process of ranking. The ranking scales used in the selected literature are quite different e.g., in the production development application, the priority for the ranking variables would be the performance e.g., mechanical properties, thermal properties, dimensional accuracy, whereas in the PD application, the cost, aesthetic and build time can be of higher priority. The parameters are prioritized based on the application's sub-categories in production development shown in Figure 8 e.g., in the aerospace industry parameters such as thermal properties and mechanical strength can be of higher priority, whereas in the automobile industry mechanical properties have higher priority than thermal properties. Aesthetics are equally important in automobile industry but may not be so in producing turbine blade in applications much as in energy industry, where chemical and physical properties are of higher priority. Hence, in the AHP process the ranking of parameters is differ based on the applications.

TOPSIS is used as a DSS in PD and deployment applications in remote or austere environments. In deployment in remote or austere environments, the authors found that requirements can take multiple forms, such as specific vs. general requirements and hard constraints vs. soft objectives [13]. These requirements are grouped into six categories that inform decision-makers of critical considerations when deploying AM technologies. The categories are **1)** process, **2)** machine, **3)** part, **4)** material, **5)** environmental, and **6)** logistical, and also all these 6 categories' constraints and objectives. Based on the application there is a possibility to prioritize this critical consideration. When we compared the same with PD application, we noted that the critical parameters were established by a questionnaire from different user groups e.g., service bureaus, governmental institutes, and industry users. The following parameters are considered for ranking: tensile strength (T), dimensional accuracy (A), surface finish (S), and economic criteria e.g., Material cost (C). Based on the decision matrix, the right process is selected by rating the parameters listed above. The decision matrix helps in determining positive and negative ideal solutions, which in turn determines the score for the parameters. These scores are tabulated and represented in charts such as Pareto diagrams, and Bretton–Clark's Conjoint Linmap. Comparing the mathematical modeling in the application like production development and sustainability, various cost models are proposed in the literature, but in sustainability, Life Cycle Assessment (LCA) method is used along with other various mathematical models, and in production development, the following variables are considered important: material cost, machine running cost, cost of post-processing, and build time. In sustainability, various parameters are calculated e.g., electrical model, fluid model, material consumption model, LCA, and economic model.

There has been a higher priority of sustainability issues in comparison to manufacturing applications, where cost model and production time are considered as higher priorities. In manufacturing applications, artificial intelligence (AI) is used in a few of the selected literature, and in PD various algorithms are used to produce a software program that is used in process selection. In manufacturing, AI is used to generate a database with knowledge discovery. Using the CAD data, the AI generates a knowledge base and then exports important features to excel where the data is tabulated and that is followed by using the AI software KNIME for selection of the right process. There is a similarity between the usage of AI in manufacturing and the usage of programming and algorithm in PD processes. In table 4, the advantages and disadvantages of the various processes that are dealt with in the selected literature are presented.

Table 4. Advantages and disadvantages of DSS processes.

Process	Advantages	Disadvantages
AHP	* Accurate results due to the use of available data from a survey. * Uses a straightforward way of ranking process for better understanding.	* Collected data must be reliable. * The model is used only for very few technologies.
TOPSIS	* Helps in using different processes in the field, where the parts are needed and can eliminate the process requiring calibration. * Implementation is straightforward to understand.	* More study needs to be done to extract exact information from users to improve accuracy with minimum inputs.
Fuzzy synthetic evaluation (FSE)	* Qualitative and quantitative data are employed, which provides more accurate results.	* Data needs to be checked and updated according to current standards.
Machine learning-based software.	* Fully automated system. * More data becomes available; accuracy will also increase. *Higher design productivity, improved access to data.	* Cost of data acquisition is high. Data security also increases the difficulties in maintaining.
Best Worst Method (BWM)	* The results are also accurate in decision-making processes due to the elimination of secondary comparisons.	* It lacks consistency issues in the reliability of results, to provide feedback to users.
Mathematical Modelling	* Reduces the wastage, helps in determining economical process	* Considers only a few processes like Multi-jetting and FDM. * The results are based on cost and other parameters. Not all the parameters are considered in the process, which can lead to less accurate results.
Novel weighted rough set based fuzzy AD.	* It maintained the rating accuracy by partial pairwise comparison and reduced the user input effort.	* It will probably result in inconsistency among the comparisons. Therefore, it is unrealistic to undertake this method with many AM attributes by expecting users to provide much repetitious information accurately.
Artificial intelligence	* Automated process	* Might become an expensive process.

5. Conclusion and Outlook

The primary goal of this paper is to help researchers and practitioners to build and implement DSSs in AM by guiding to what extent the research has been carried out, in what context, and what DSSs are utilized. This SLR provides an in-depth insight on the topic of DSS in AM. AM and its potential to build complex structures and bring new designs to market in various applications have been and still is a very important. But the DSS required to make the process a success is yet to be fully discovered. When the criteria of each of the processes change, the decision-making ability also changes. There is no standardized fact-based DSS for all the applications. A selected methodology should be implemented in the early stages of optimizing the processes. Moreover, DSSs developments should be considered to make the processes more efficient, and in a timely & cost-effective manner. One of the greatest benefits of the DSS in AM is that it does not only help in the reduction of PD time, design rework, and cost, but also it assists in better findings in terms of technique to meet customer and organizational requirement.[14]. DSSs can also help in reducing waste usually created by trial-and-error methods helping in reducing the material usage and making the process more sustainable.

Further research is required in DSS for AM in utilizing modern technologies e.g., AI and machine learning to help achieve the goal in the development of a modernized fact-based technique (vs. mostly based on experiences) for an accurate process selection. Another avenue for future research would be to reduce the cost for the implementation of modern technologies. Machine learning and AI are the two examples of the most desirable techniques in terms of accuracy, but they can be very expensive to implement.

The process of using historical data for the process selection is an alternative. Here a database is maintained of various designs performed in the past. By using machine learning, the decision-maker can use the past data for a selection of an alternative solution.

This can also be considered as one of the techniques, which can be explored in future research as a possible DSS for AM.

If DSS processes are interlinked, this could provide highly accurate results. This is currently little followed in research that has been assessed in this SLR. One reason could be that the researchers' and/or practitioners' focus have been on a specific process. This can be solved by linking different departments to generate an accurate and generic methodology for the DSS in AM. For example, the ranking process can generate accurate results, but one limitation could be its time-consuming nature as there would be some mathematical calculations to be performed to obtain the results. However, by involving the software team to help generate an algorithm to solve the mathematical problems, the result could be generated faster. Hence, one of the main future scopes could be to link various MCDM processes to certain programming software. This could lead to obtaining desirable results at a faster rate, and would probably be more cost-effective, in comparison to the implementation of AL and machine learning techniques.

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