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Review

Multi-Attribute Decision-Making Methods in Additive Manufacturing: The State of the Art

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Abstract: Multi-attribute decision-making (MADM) refers to making preference decisions via assessing a finite number of pre-specified alternatives under multiple and usually conflicting attributes. Many problems in the field of additive manufacturing (AM) are essentially MADM problems or can be converted into MADM problems. Recently, a variety of MADM methods have been applied to solve MADM problems in AM. This generates a series of interesting questions: What is the general trend of this research topic from the perspective of published articles every year? Which journals published the most articles on the research topic? Which articles on the research topic are the most cited? What MADM methods have been applied to the field of AM? What are the main strengths and weaknesses of each MADM method used? Which MADM method is the most used one in this field? What specific problems in AM have been tackled via using MADM methods? What are the main issues in existing MADM methods for AM that need to be addressed in future studies? To approach these questions, a review of MADM methods in AM is presented in this paper. Firstly, an overview of existing MADM methods in AM was carried out based on the perspective of specific MADM methods. A statistical analysis of these methods is then made from the aspects of published journal articles, applied specific methods, and solved AM problems. After that, the main issues in the application of MADM methods to AM are discussed. Finally, the research findings of this review are summarised.

Keywords: additive manufacturing; decision problem; optimisation; decision-making method; multi-attribute decision-making

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1. Introduction

Multi-attribute decision-making (MADM) is a process of making preference decisions via evaluating a finite number of pre-specified alternatives under multiple and usually conflicting attributes, in which inter-attribute or intra-attribute comparisons are required and implicit or explicit trade-offs are involved [1]. An MADM problem generally contains a limited number of alternatives, a certain number of attributes, weights or degrees of importance of the attributes, and measures of performance of the alternatives with respect to the attributes. A solution to the problem is the best alternative or a ranking of all alternatives. The earliest method for solving an MADM problem was probably the simple additive weighting method (also known as the weighted sum model or weighted averaging operator), which was used to look at an MADM problem formally by Churchman et al. [2] in 1957. Since then, a variety of other methods have been presented in the literature. Comprehensive surveys of existing MADM methods can be found in [3–5].

Additive manufacturing (AM), also known as three-dimensional (3D) printing and rapid prototyping, refers to a set of technologies that directly create 3D objects layer upon layer from digital three-dimensional models [6,7]. The use of an AM technology to realise a product involves a set of activities, which mainly include the design, process planning, build, post-processing, and qualification [8]. In AM product realisation activities, there are many problems that belong to MADM problems or can be converted to MADM problems. For example, in the design activity, a designer needs to select a proper AM process or machine from a limited number of alternatives to build a part, in which certain multiple attributes, such as build time, part cost, dimensional accuracy, surface quality, tensile strength, and elongation, are taken into consideration [9]. An AM process or machine selection problem like this is a typical MADM problem. As another example, in the process planning activity, a process planner needs to determine an appropriate orientation from an infinite number of possible orientations to build a part, in which certain multiple factors, such as support volume, build time, build cost, surface quality, and part property, are considered comprehensively. Although the solution space of this problem is infinite, specific techniques such as feature recognition, convex hull generation, quaternion rotation, and facet clustering can first be used to transform it into a finite space, and then a proper orientation can be selected from a finite number of alternative orientations [10]. Therefore, an AM part orientation problem can be converted into an MADM problem.

To solve the MADM problems in AM, a large number of MADM methods have been applied in recent decades. The MADM methods used mainly include aggregation operators (AOs) [11–22], analytical hierarchy process (AHP) [23–43], technique for order of preference by similarity to an ideal solution (TOPSIS) [44–56], deviation function (DF) [57,58], fuzzy synthetic evaluation (FSE) [59,60], graph theory and matrix approach (GTMA) [61], multi-objective optimisation by ratio analysis (MOORA) [62], knowledge value measuring (KVM) [63], vlsekriterijuska optimizacija i komoromisno resenje (VIKOR) [64–66], complex proportional assessment (COPRAS) [67,68], analytical network process (ANP) [69], axiomatic design (AD) [70], elimination et choix traduisant la réalité (ELECTRE) [71], preference selection index (PSI) [72,73], best–worst method (BWM) [74,75], three-way decision model (3WDM) [76,77], and hybrid methods [78–110]. The application of different MADM methods in AM triggers a series of interesting questions: What has been the general trend of this research topic from the perspective of articles being published every year? Which journals published the most articles on the research topic? Which articles on the research topic are the most cited? What MADM methods have been applied to the field of AM? What are the main strengths and weaknesses of each MADM method used? Which MADM method is the most used one in this field? What specific problems in AM have been tackled using MADM methods? What are the main issues in existing MADM methods for AM that need to be addressed in future studies?

This paper attempts to approach the questions above via presenting a systematic review of MADM methods in AM. Although there are already two related reviews in [111,112], the review in the present paper is still of necessity because: (1) The review in [111] provides an overview on the use of operations research in AM. In this review, the application of MADM methods in AM is just a small part, and most of the questions listed above are not addressed; (2) The review in [112] conducts a survey of decision support systems for the selection of AM processes. Twenty-nine journal articles and eleven conference articles regarding this topic were evaluated in this review. The decision support systems reported in these articles are based on MADM, mathematical modelling, software, or design approach; (3) Compared to the two related reviews, the review in the present paper approaches the questions systematically and covers a variety of problems in AM (not just the AM process selection problem) that have applied MADM methods. The remainder of the paper is organised as follows: An overview of existing MADM methods in AM is provided in Section 2; Section 3 reports a statistical analysis of these methods; A discussion of the main issues in the application of MADM methods to AM is documented in Section 4; Section 5 ends the paper with a conclusion.

2. MADM Methods in AM

2.1. AOs in AM

AOs, also known as aggregation functions, are mathematical functions for grouping together multiple values to obtain a single summary value [113]. The most well-known AO is the weighted averaging operator (i.e., a simple additive weighting method or weighted sum model). Other AOs commonly used in MADM include the ordered weighted averaging operator, power averaging operator, weighted Heronian mean operator, weighted Bonferroni mean operator, weighted Maclaurin symmetric mean operator, and weighted Muirhead mean operator. An important feature of AOs is that they can generate summary attribute values and a ranking of alternatives, which greatly facilitate the final decision. Another important feature is that each AO has its specific capability in solving MADM problems. For example, the ordered weighted averaging operator can capture the ordered positions of attribute values; the power averaging operator can reduce the influence of extreme attribute values on the aggregation results; the weighted Heronian mean operator and weighted Bonferroni mean operator can capture the interactions between two attributes; the weighted Maclaurin symmetric mean operator and weighted Muirhead mean operator can capture the interactions among multiple attributes. Because of such feature and capabilities, AOs have been widely applied to solve MADM problems in many fields. In the field of AM, AOs have been applied to tackle the problems below.

2.1.1. AOs in Part Orientation

Pham et al. [11] developed a decision support system based on the weighted averaging operator to solve the part orientation problem in stereolithography (SLA), where alternative orientations are obtained via feature recognition and the best orientation is selected via considering the overhanging region area, support volume, build time, build cost, and problematic features. Byun and Lee [12,13] presented an approach based on the weighted averaging operator to determine the optimal orientation to build an AM part. In this approach, the alternative orientations of an AM part are generated according to the surfaces of the convex hull of its 3D model and the optimal orientation for building the part is determined under the consideration of surface roughness, build time, and manufacturing cost. Al-Ahmari et al. [14] developed a decision system based on the weighted averaging operator for the automatic generation of part build orientations in selective laser melting (SLM), where feasible orientations are obtained via feature recognition and the maximisation of the tolerances of all features and the final orientation is generated based on the predicted part accuracy and build time.

In Qie et al. [15], a quantitative approach based on the ordered weighted averaging operator for part orientation in SLA were presented, where the alternative orientations of an SLA part are acquired via quaternion rotation and the best orientation of the part is selected via the simultaneous optimisation of surface roughness, support volume, and build time. In Zhang et al. [16], a statistical approach based on the *k*-means clustering algorithm and weighted averaging operator for build orientation determination in AM was developed. This approach obtains alternative orientations via facet clustering and determines the optimal orientation according to a decision index that implicitly reflects the effect of build orientation on the surface quality and support structure. In Qin et al. [17], a generic approach based on a fuzzy power partitioned weighted Muirhead mean operator and a fuzzy power prioritised averaging operator for the determination of the optimal build orientation in AM was proposed. This approach has an advantage in capturing the correlative and priority relationships among the considered attributes.

2.1.2. AOs in AM-Related Assessment

Moreno-Cabezali and Fernandez-Crehuet [18] carried out a risk assessment on AM research and development projects based on a fuzzy weighted triangular averaging operator. A set of risks with negative influence on project objectives are identified from the literature and assessed via a survey answered by ninety experts. The responses of the experts are aggregated using the AO. The aggregation results show that defects occurring during the building of a part presents the most critical risk.

2.1.3. AOs in Process Selection

Qin et al. [19] presented a generic approach based on two fuzzy Archimedean power-weighted Bonferroni mean operators for the selection of AM processes. This approach has characteristics in providing good versatility and flexibility, capturing the interrelationships of performance parameter types and the risk attitudes of decision makers, and reducing the influence of extreme performance parameter values on the aggregation results. Qin et al. [20] constructed two linguistic interval-valued intuitionistic fuzzy Archimedean prioritised operators and applied them in AM machine selection. These two AOs can process the situation where the attribute weights are unknown and the attributes are in different priority levels. Qin et al. [21] presented a linguistic interval-valued intuitionistic fuzzy Archimedean power weighted Muirhead mean operator and studied its application in 3D printer selection. Compared to the AOs in [20], this AO can also capture the interrelationships among multiple attributes.

2.1.4. AOs in Multiple Problems

Huang et al. [22] developed a generic approach based on a fuzzy Hamacher power weighted Maclaurin symmetric mean operator for MADM problems in design for AM. This approach was demonstrated using an AM machine and material selection example and an optimal build orientation determination example. Compared to the AO in [21], the developed approach also has the capability to capture the risk attitudes of decision makers.

2.2. AHP in AM

AHP is a structured MADM method based on mathematics and psychology for organising and analysing complex decisions [114]. In this method, an MADM problem is first decomposed into different hierarchies in the order of the overall objective, the sub-objective in each level, the attributes, and the alternatives. Then, the priority of each element in each level to an element of the previous level is calculated via solving the eigenvector of a positive reciprocal pairwise comparison matrix. Finally, the weighted averaging operator is used to calculate the final priorities of all alternatives to the overall objective, and the alternative with the highest final priority is determined as the best alternative. AHP provides a systematic, simple, and practical method for structuring an MADM problem, quantifying the elements, relating the elements to the overall objective, and evaluating the alternatives. It has been extensively studied, refined, and applied in many areas since its introduction. In the area of AM, AHP has been applied to solve the problems below.

2.2.1. AHP in Process Selection

Braglia and Petroni [23] proposed a management support approach based on AHP for the selection of AM technologies. This approach decomposes the selection problem into a four-level structure. The first level represents the overall objective of AM technology selection. The overall objectives are divided into five sub-objectives: price, friendliness, characteristics, cost, and time, which are included at the second level. The sub-objectives of friendliness, characteristics, and cost make up the third level. The last level consists of alternative AM machines. Armillotta [24] presented an AM technique selection approach based on an adaptive AHP decision model. This approach also decomposes the selection problem into a four-level structure: application, categories of AM techniques, attributes, and alternative AM techniques. It is improved with a procedure that adapts the parameters of the AHP model to AM technique specifications. Lokesh and Jain [25] developed a systematic approach based on AHP for the selection of AM technologies. This approach also solves the selection problem via a four-level structure. The first level stands for the overall issue. The product requirement issues, process requirement issues, social and environmental issues, and user- and company-related issues constitute the second level. Their sub-issues are included at the third level. The last level consists of alternative AM technologies.

In Mancanares et al. [26], an approach based on AHP for the selection of AM processes was proposed. Five attributes that describe the technical specifications of a part, including the multicoloured part, accuracy, surface quality, resistance to impact, and flexural strength, are considered in the pairwise comparison. In Liu et al. [27], a decision-making methodology based on AHP to facilitate AM process selection was developed. This methodology consists of initial screening, the generation of feasible processes, the evaluation of the feasible processes, and the selection of a production machine. The selection is performed using AHP, where factors that would cause manufacturability issues and increase the manufacturing cost are considered in the pairwise comparison. In Bikas et al. [28], a decision support approach based on AHP for knowledge-based AM process selection was presented. This approach consists of a material selection step, a process suitability examination step, a suitable machine search step, and a best machine determination step. The first, second, and last step were each carried out using AHP with a three-level structure.

Psarommatis and Vosniakos [29] developed a powder deposition system based on AHP for an open selective laser sintering (SLS) machine. The design in the system includes a conceptualisation phase and a detailed design phase. In the conceptualisation phase, AHP is adopted to evaluate alternative mechanical systems and choose the most suitable one. Raja et al. [30] proposed an approach based on AHP for the selection of a fused deposition modelling (FDM) machine. This approach consists of an alternative machine search step and an optimal machine determination step. The first step is carried out based on the price, size, volume, extruder type, and weight of machines. An optimal machine is selected using AHP, where the criteria and the pairwise comparison matrix for AHP are derived from decision makers.

2.2.2. AHP in Adhesive Selection

Arenas et al. [31] presented an approach based on AHP to select a structural adhesive that best conjugates mechanical benefits and adaptation to FDM from five different types of structural adhesives, including cyanoacrylate, polyurethane, epoxy, acrylic, and silicone. This approach tackles the selection problem through four levels. The first level represents the overall objective and the last one includes the five alternative adhesives. The technological criterion, adjustment to FDM, and economic criterion form the second level. Their sub-criteria are included at the third level. The experimental results suggest that polyurethane is the best adhesive to bond ABS parts fabricated by FDM.

2.2.3. AHP in Part Selection

Knofius et al. [32] developed an approach based on AHP for the selection of parts for AM in service logistics. The overall objective is divided into the securing supply, reducing the downtime, and reducing the cost. Both securing supply and reducing downtime are further decomposed into supply options and supply risk, while reducing the cost is further divided into the remaining usage period, manufacturing and order costs, and supply options. Muvunzi et al. [33] constructed an evaluation model based on AHP for the selection of part candidates for AM in transport sector. Six selection criteria including geometric complexity, production volume, function, opportunity for design improvement, time to manufacture, and material removal are considered in the model. These criteria are ranked according to the requirements of the transport equipment manufacturing industry via the use of AHP. Foshammer et al. [34] presented a knowledge management-based approach to identify the aftermarket and legacy parts suitable for AM. The part identification entailed AHP, semi-structured interviews, and workshops. Compared to the existing approaches, the presented approach integrates knowledge management-based part identification with current operations and supply chains.

2.2.4. AHP in Multiple Problems

Uz Zaman et al. [35] introduced a generic decision methodology based on AHP for the selection of AM processes and materials. The criteria for AM process selection include geometry complexity, minimum layer thickness, accuracy, build volume, build speed, machine cost, and labour cost. The criteria for AM material selection come from nine material indices.

The introduced methodology provides a guideline for designers to achieve a strong foothold in the AM industry. Hodonou et al. [36] presented an integrated material-design-process selection methodology based on AHP for aircraft structural components manufactured by subtractive and additive processes. This methodology solves the selection problem via a three-level structure. The first level is the overall objective of the material-design-process selection. The second level consists of three selection attributes including the mass, buy-to-fly ratio, and manufacturing cost. Alternatives are included at the third level. The methodology is adopted to redesign an aircraft component for machined Al7075-T6 and for SLM AlSi10Mg powders. Kadkhoda-Ahmadi et al. [37] developed a multi-criterion evaluation system based on AHP to solve the process and resource selection problem in design for AM. The working process of this system mainly includes a screening step, a comparative assessment step, and a ranking step. In the first step, the AM process, machine, and material are screened according to some technical and economic evaluation criteria. The second and third steps are carried out using AHP where the sub-criteria including the build time, accuracy performance, and cost are considered.

2.2.5. AHP in Material Selection

Alghamdy et al. [38] presented a material selection methodology based on AHP for AM applications. This methodology consists of two steps, including the screening of available materials and the ranking of alternative materials. The first step was implemented using a heuristic and analytical algorithm based on AHP, where the performance, physical, and thermal requirements are considered. The second step is carried out via a decision matrix, where the alternative materials are ranked based on the cost and best performance.

2.2.6. AHP in AM-Related Assessment

Foteinopoulos et al. [39] proposed an approach for the evaluation of the key performance indicators in the construction sector AM. This approach is based on a modified version of AHP, which was found to greatly decrease the needed comparisons and minimise the preparation time when the number of variables is large. Sonar et al. [40] developed an approach based on AHP to identify and prioritise AM implementation factors. In this approach, a total of eleven AM implementation factors, including AM technology, top management commitment, technological awareness, information sharing, organisation capability and human resource, education and training, supply chain coordination, market support, customer and service management, process improvement practices, and financial capability are identified and ranked via AHP. Bappy et al. [41] constructed a model based on AHP and evidential reasoning to assess the social impacts of AM technologies. In this model, AHP is used to rate and structure the relevant attributes of social impacts, while evidential reasoning is applied to aggregate the subjective judgmental belief structure data. The model output includes the average state of the social impact together with the uncertainty for each attribute.

2.2.7. AHP in Production Scheduling

Ransikarbum et al. [42] developed a decision support model based on multi-objective optimisation and AHP for production and distribution planning in material extrusion, SLA, and SLS. In this model, a multi-objective optimisation technique is applied to schedule component batches to a network of AM machines, and AHP is adopted to analyse the trade-offs among conflicting objectives.

2.2.8. AHP in Design Selection

Rochman et al. [43] presented an approach based on AHP for the selection of 3D printing COVID-19 mask design. The selection criteria are identified from the aspects of customer, production, and cost, which include the usefulness, easy to use, material selection, print time, print cost, and additional material cost.

2.3. TOPSIS in AM

TOPSIS is an MADM method that ranks the alternatives according to their geometric distances from the best solution and from the worst solution [115]. This method has an assumption that the attributes are monotonically increasing or decreasing. The normalisation of attribute measures is usually needed in it since they are often of incongruous dimensions. The best alternative determined by the method should have the shortest geometric distance from the best solution and the longest geometric distance from the worst solution. TOPSIS is a method of compensatory aggregation that allows trade-offs between attributes, where a bad result in one attribute can be negated by a good result in another one. This provides a more realistic modelling approach than non-compensatory methods. TOPSIS has been widely applied to a variety of fields since its introduction. In the field of AM, TOPSIS has been used in the problems below.

2.3.1. TOPSIS in Process Selection

Vahdani et al. [44] presented a group decision-making method based on a fuzzy modified TOPSIS. In this method, the performance measures of the alternatives with respect to the attributes as well as the weights of the attributes are quantified via linguistic variables and are converted into triangular fuzzy numbers. To differentiate between alternatives in the evaluation process, a collective index is introduced. The method is demonstrated via an industrial robot selection example and an AM process selection example. Ic [45] proposed an experimental design approach based on TOPSIS for the selection of computer-integrated manufacturing technologies. This approach combines TOPSIS and experiment design, which greatly reduces the computation cost and time in TOPSIS. The approach was validated using four computer-integrated manufacturing technology selection problems, including industrial robot selection, AM process selection, machine tool selection, and plant layout design. Yildiz and Ugur [46] evaluated 3D printers used in AM by using interval type-2 fuzzy TOPSIS. In the evaluation process, the max printing speed, max build volume, layer resolution, price, and positioning precision are identified as attributes, and the performance measures of the alternative 3D printers with respect to these attributes are described using interval type-2 fuzzy numbers.

In Saxena et al. [49], an approach based on TOPSIS for the selection of the best technique for given moulds to be manufactured was developed. This approach formulates the sustainability metrics for mould production and compares conventional sand moulds with 3D-printed sand moulds. TOPSIS is linked to an automatic combinatorial method to generate high-resolution maps. In Raja and Rajan [50], a decision-making model based on fuzzy TOPSIS for selection of an FDM machine was constructed. In this model, the price, build volume, extruder type, printing speed, operating temperature, filament material, tolerance, environmental factor, and machine safety are identified as attributes. The results of the expert evaluations are expressed in linguistic values and converted into triangular fuzzy numbers.

2.3.2. TOPSIS in Part Orientation

Yu et al. [47] studied the personalised design of part build orientation in AM. TOPSIS is used to calculate a score for each orientation during the rotation of a part. The proportional–integral–derivative controller rotates the part according to the error between the target and score. A suitable orientation is determined when the error is eliminated.

2.3.3. TOPSIS in AM-Related Assessment

Priarone et al. [48] assessed the environmental and economic impact of wire arc AM, where TOPSIS is applied to generate high-resolution maps of the results within the decision-making space. Alsaadi [51] studied the prioritisation of challenges for the effectuation of sustainable AM via grey TOPSIS. In this study, fifteen sustainable AM challenges were identified from the literature and ranked using the TOPSIS in grey environment. The ranking results show that training towards sustainable AM benefits and limited materials recycling potential are significant challenges. Agrawal [52] presented an approach to analyse the sustainable design guidelines for AM applications. In this approach, twenty-six guidelines are identified and divided into four groups. Grey axiomatic design is used to determine the weight of each group and grey TOPSIS is applied to prioritise the guidelines. The prioritisation results suggest that the design for the reusability and optimisation of build orientation to reduce the build time and surface roughness are the top identified guidelines.

2.3.4. TOPSIS in Parameter Optimisation

Kamaal et al. [53] studied the influence of build orientation, infill percentage, and layer height on the tensile strength and impact strength of FDM carbon fibre–polylactic acid composite. TOPSIS is used to find the best set of build orientation, infill percentage, and layer height that would obtain the maximum strength using minimum material. Sugavaneswaran et al. [54] studied the combined effect of FDM and vapour smoothening process parameters on part quality. The process parameters include build the orientation angle, build surface normal, and exposure time, whilst the part quality indicators are the surface roughness and dimensional error percentage. TOPSIS is applied in this study to determine the optimal set of process parameters. Kumar et al. [55] presented a hybrid approach for twin screw extrusion parametric optimisation. In this approach, the analysis of variance is used to produce alternative sets of process parameters, and TOPSIS is applied to carry out multi-objective selection.

2.3.5. TOPSIS in Material Selection

Jha et al. [56] developed a material selection approach based on TOPSIS for the biomedical application of AM. In this approach, the materials for the biomedical application of AM are first identified according to survey of the literature and the experience of the experts, and TOPSIS is applied to prioritise the identified materials.

2.4. Other Single Methods in AM

In addition to AOs, AHP, and TOPSIS, other single MADM methods, including DF [116], FSE [117], GTMA [118], MOORA [119], KVM [120], VIKOR [121], COPRAS [122], ANP [123], AD [124], ELECTRE [125], PSI [126], BWM [127], and 3WDM [128], have also been applied to address the following problems in the field of AM.

2.4.1. Other Single Methods in Multiple Problems

West et al. [57] presented a process planning approach to aid SLA users in the selection of proper process variables to obtain the desired part performance. This approach achieves a balance of objectives described by geometric tolerances, surface finishes, and build time. The process variables to be determined include build orientation, layer thicknesses, z-level wait time, sweep period, hatch overcure, and fill overcure. The determination process is carried out using an MADM method based on the deviation function. Palanisamy et al. [74] applied BWM to select a suitable AM machine and material for a product. The selection of a suitable machine is based on the criteria including the cost, accuracy, variety of materials, and material wastage. The selection of the best material is based on respondent requirement, in which the criteria that affect the overall cost of the product are considered.

2.4.2. Other Single Methods in Process Selection

Lan et al. [59] developed a decision support system for AM process selection, where the alternative AM processes are determined via a knowledge-based expert system, and the most suitable AM process is selected using an FSE model. Rao and Padm [61] presented a GTMA-based methodology for the selection of an AM process that best suits the end use of a given product, where a selection index obtained from a digraph of selection attributes is introduced to evaluate and rank the alternative AM processes. Chakraborty [62] studied the application of MOORA for MADM in a manufacturing environment, where the selection of an industrial robot, a manufacturing system, a numerical control machine, a machining process, an AM process, and an inspection system are addressed.

In Khrais et al. [60], an FSE approach to select an AM process for producing prototypes was presented. In this approach, fuzzy if–then rules and fuzzy sets are used to translate the appropriateness of each process into each attribute, and the best process is identified according to the overall efficiencies of alternative processes. In Roberson et al. [58], a model for evaluating and prioritising 3D printing technologies based on some purchasing considerations was constructed, in which the prioritisation was implemented using an MADM method based on DF. In Vinodh et al. [64], the application of fuzzy VIKOR for the selection of AM processes in an agile environment was studied. It was found that FDM is the most suitable process for fabricating the prototypes of pump impeller.

Zhang et al. [63] presented a decision support approach for the selection of AM processes. This approach is based on KVM, i.e., measuring the manufacturing knowledge value extracted from AM processes. It has an advantage in using structured expert knowledge or production experience to assist in the AM process selection. Makhesana [67] applied an improved COPRAS method to AM process selection. Compared with the original COPRAS method, the method used can deal with even qualitative data for attributes. Kumar et al. [69] developed an ANP-based approach for the selection of AM technologies. This approach considers both qualitative and quantitative attributes in the selection.

In Gitinavard et al. [68], an interval-valued hesitant fuzzy COPRAS method for MADM was presented. In this method, the performance measures of the alternatives with respect to the attributes and the weights of the attributes are described by linguistic variables and then converted into interval-valued hesitant fuzzy elements. The method is validated via three case studies about robot selection, industrial site selection, and AM process selection. In Zheng et al. [70], a weighted rough set-based fuzzy AD approach for AM process selection was proposed. This approach has an advantage in dealing with incomplete attribute information and objective assessment. In Prabhu et al. [73], an MADM method based on PSI for the selection of a 3D printer was developed. This method considers six adverse attributes including the maximum print volume, speed of operation, minimum thickness, extruder capacity, printer cost, and filament material cost.

Qin et al. [76] presented a 3WDM-based MADM method under linguistic interval-valued intuitionistic fuzzy environment. The application of this method is illustrated via a 3D printer selection example.

2.4.3. Other Single Methods in Parameter Optimisation

Patel et al. [72] studied the application of PSI to select the optimal process parameters for FDM polylactic acid, where five attributes including the tensile strength, tensile module, surface roughness, compressive strength, and compressive module are considered. Raykar and D'Addona [65] applied VIKOR to select the optimal set of layer thickness, bed temperature, printing speed, and infill percentage for FDM, where the responses include the material weight, material length, and total time. Deomore and Raykar [66] applied VIKOR to select the best set of the layer thickness, infill percentage, bed temperature, printing speed, infill pattern, build orientation, air gap, and raster angle for FDM, where the responses are also the material weight, material length, and total time.

2.4.4. Other Single Methods in Material Selection

Exconde et al. [71] studied the selection of virgin polymer resins and recycled post-consumer plastics for use in 3D printer filaments. The ELECTRE method was used to select the best material. The study suggests that the virgin low-density polyethylene is the best alternative filament. Qin et al. [77] proposed a 3WDM-based approach for the selection of materials in metal AM. The effectiveness of the approach is demonstrated via a quantitative comparison with several existing approaches. The demonstration results show that the proposed approach is as effective as the existing approaches and is more flexible and advantageous than them.

2.4.5. Other Single Methods in AM-Related Assessment

Agrawal and Vinodh [75] studied the prioritisation of drivers of sustainable AM. Forty drivers were analysed and rated from eight perspectives using BWM. The rating results show that the key drivers are eco-design, green innovation, and energy conservation.

2.5. Hybrid Methods in AM

In the literature, a number of researchers applied two or more single MADM methods simultaneously or applied a hybrid of two or more single MADM methods to solve some problems in AM. These single MADM methods include AOs [113], AHP [114], TOPSIS [115], FSE [117], GTMA [118], MOORA [119], VIKOR [121], COPRAS [122], ANP [123], ELECTRE [125], BWM [127], simple pair analysis (SPA) [129], verein deutscher ingenieure (VDI) [130], preference ranking organisation method for enrichment evaluation (PROMETHEE) [131], grey relational analysis (GRA) [132], decision-making trial and evaluation laboratory (DEMATEL) [133], similarity-based approach (SIMA) [134], proximity indexed value (PIV) [135], data envelopment analysis (DEA) [136], linear normalisation (LN) [137], stepwise weight assessment ratio analysis (SWARA) [138], measurement alternatives and ranking according to compromise solution (MARCOS) [139], information entropy method (IEM) [140], combinative distance-based assessment (CODAS) [141], and weighted aggregated sum product assessment (WASPAS) [142]. The problems that have been studied are elaborated upon below.

2.5.1. Hybrid Methods in Process Selection

Byun and Lee [78] developed a decision support system for the selection of an AM process. In this system, the performance measures of the alternatives with respect to the attributes are quantified by either numerical values or linguistic variables, the weights of the attributes are determined via AHP, and the alternatives are ranked by a modified TOPSIS method. Borille et al. [79] applied six MADM methods including TOPSIS, GTMA, AHP, multiplicative AHP, SPA, and VDI to select AM technologies. It is demonstrated that not all methods produce the same ranking of AM technologies. Rao and Patel [80] presented a hybrid method to solve MADM problems in the manufacturing environment. This method is obtained by integrating PROMETHEE with AHP and FSE. It is demonstrated via four examples about cutting fluid selection, manufacturing program selection, end-of-life scenario selection, and AM process selection.

In Mahapatra and Panda [81], GRA and fuzzy TOPSIS are applied to select AM processes. The results of GRA are compared with that of fuzzy TOPSIS. It is concluded that SLS is the process for the best dimensional accuracy and surface quality. In Paul et al. [84], a comparison of three MADM methods considering a case of selection of 3D printers is carried out. The methods are TOPSIS, SIMA, and PROMETHEE, in which the weights are determined using ANP. In Vimal et al. [85], a decision support system for AM process selection considering environmental criteria was developed. The ranking mechanism of this system is based on a hybrid of ANP and TOPSIS. The ranking results show that SLA is the best process based on environmental considerations.

Cetinkaya et al. [87] applied a hybrid of fuzzy AHP and PROMETHEE in 3D printer selection, where the selection criteria are prioritised via fuzzy AHP and alternative 3D printers are ranked via PROMETHEE. Anand and Vinodh [89] adopted an integration of fuzzy AHP and fuzzy TOPSIS to rank AM processes for micro-fabrication, where the weights are determined using fuzzy AHP and alternative AM processes are rated using fuzzy TOPSIS. Wang et al. [90] presented a hybrid MADM method for AM process selection. In this method, AHP is used to capture the preferences and a modified TOPSIS is introduced to prioritise solutions and provide suggestions.

In Moiduddin et al. [91], a decision advisor based on fuzzy AHP and GRA for AM system selection was introduced, where fuzzy AHP based on trapezoidal fuzzy numbers was adopted to determine the weights of attributes, and GRA was applied to find the best AM system. In Prabhu and Ilangkumaran [92], the proficiency of 3D printers to produce automotive parts is assessed, where fuzzy AHP, fuzzy VIKOR, and fuzzy ELECTRE are applied to evaluate and rank the alternative 3D printers. In Prabhu and Ilangkumaran [93], fuzzy AHP was integrated with GRA and TOPSIS to evaluate and select suitable 3D printers, where fuzzy AHP is used to determine the weights of the selection attributes and GRA and TOPSIS are adopted to obtain a ranking of alternative 3D printers.

Raigar et al. [95] developed a decision support system for the selection of an AM process. This system is based on a hybrid MADM method that combines BWM with PIV, where BWM is employed to determine the optimal attribute weights and PIV is used to prioritise the available AM processes. Ransikarbum and Khamhong [99] evaluated the AM machine selection problem for healthcare applications. In this evaluation, fuzzy AHP is used to assess the relative importance of selection attributes, and TOPSIS is employed to assess the alternative AM machines based on the preferences of experts and users. Chandra et al. [104] studied the selection of an appropriate AM process by considering sustainable concepts. A hybrid MADM method based on SWARA and COPRAS is used to prioritise four AM processes including SLA, FDM, SLS, and laminated object manufacturing. It was found that FDM is the best process for sustainable purposes.

2.5.2. Hybrid Methods in AM-Related Assessment

Liao et al. [82] established a hybrid MADM framework for evaluating and enhancing 3D printing service providers. This framework was realised using the DEMATEL-based network process and VIKOR. Cruz and Borille [88] applied three MADM methods to compare AM with the machining process of a titanium part used in the aerospace industry. The three methods are AHP, SPA, and VDI. It was found from the comparison results that topology optimisation-SLM is a strong candidate for manufacturing titanium parts for aerospace application. Wang et al. [94] presented a fuzzy systematic approach to assess the factors critical to the applicability of AM technologies in the aircraft industry. This approach combines a fuzzy weighted geometric operator with fuzzy AHP.

In Zhang et al. [102], an optimal set algorithm based on AHP, TOPSIS, and the Baldwin effect was developed to evaluate the cloud 3D printing order task execution. This algorithm can perform the automatic matching and optimisation of alternative services. In Yoris-Nobile et al. [110], life cycle assessment and MADM analysis to determine the performance of 3D printed cement mortars and geopolymers were carried out, where the life cycle assessment is performed to study the environmental impact of materials, and the MADM analysis is based on AHP, IEM, TOPSIS, and WASPAS and applied to select the most suitable dosages.

2.5.3. Hybrid Methods in Multiple Problems

Zhang and Bernard [83] constructed an integrated model for MADM problems in process planning for AM. This integrated model is an aggregation of a deviation model and a similarity model. The deviation model, which is inspired by TOPSIS, measures the deviation extent of each alternative to the aspired goal based on the geometric distance between them. The similarity model, which is based on GRA, measures the similarity between alternatives and the expected goal via analysing the curve shape of each alternative. Algunaid and Liu [103] developed a decision support system for the selection of AM processes, machines, and materials from a large-scale option pool. This system is based on a hybrid MADM method that integrates DEMATEL, AHP, and a modified TOPSIS.

2.5.4. Hybrid Methods in Part Orientation

Zhang et al. [86] presented a feature-based build orientation optimisation method for AM. In this method, alternative build orientations are obtained from shape feature recognition, and the best build orientation are selected from the alternatives using the integrated model in [83]. Qin et al. [98] developed an automatic determination approach of the build orientation for an SLM part. In this approach, the alternative build orientations for an SLM part are generated via facet clustering, while the optimal build orientation for the part is determined using AHP and the weighted averaging operator. Ransikarbum et al. [100] established an integrated MADM framework for part build orientation analysis in AM. In this framework, the quantitative data are assessed using DEA, the preferences of decision makers are analysed using AHP, and a suitable build orientation is determined using LN.

In Sheng et al. [109], a build orientation optimisation approach for extrusion-based AM is proposed. This approach produces alternative orientations according to the minimum bounding rectangles of the facet clusters. The optimal orientation is selected using an integrated MADM model composed of the weighted averaging operator and GRA.

2.5.5. Hybrid Methods in Material Selection

Zhang et al. [96] studied the material selection of 3D printed continuous carbon fibre-reinforced composites. A systematic hierarchical structure of multiple criteria considering the environmental, economic, social, and physical impacts is established. An integrated MADM method containing fuzzy BWM, GRA, and fuzzy VIKOR is presented to solve the material selection problem. Agrawal [97] carried out a critical analysis of the rank reversal approach for sustainable AM material selection. Four MADM methods including the weighted averaging operator, MOORA, TOPSIS, and VIKOR were applied to compare the materials. The comparison results show that Accura HPC, TPU Elastomer, and Duraform EX are, respectively, the best sustainable material for SLA, FDM, and SLS. Malaga et al. [106] studied the material selection for metal AM process. IEM and CODAS are applied to determine the priority order of alternative materials. The results show that aluminium alloy AlSi12Cu2Fe, tool steel H13, and aluminium alloy AlSi10Mg are the top-ranking materials for metal AM.

In Mastura et al. [107], the concurrent material selection of a natural fibre filament for FDM was investigated. An integration of AHP and ANP is introduced to select suitable natural fibres for FDM.

2.5.6. Hybrid Methods in Parameter Optimisation

Sakthivel and Vinodh [101] applied the grey-based Taguchi method to optimise the slice height, part fill style, and build orientation of FDM. The response parameters include the build time, surface roughness, and hardness. The optimisation results are verified using a hybrid approach based on AHP and TOPSIS. Koli et al. [105] investigated the effect of the current speed, welding speed, and gas flow rate on the ultimate tensile strength, micro-hardness, compressive residual stress, and total elongation of SS308L samples fabricated by the wire arc AM-cold metal transfer process. The optimal set of the process parameters is determined via an integrated MADM method based on fuzzy AHP, fuzzy MARCOS, and the analysis of means. Patil et al. [108] presented an MADM method based on AHP and VIKOR for the selection of the best process parameters for FDM. The layer thickness, printing speed, infill percentage, and zig–zag pattern in FDM are simultaneously optimised by the method.

3. Statistical Analysis

3.1. Published Journal Articles

A large number of research articles about MADM methods in AM have been published in a number of journals in recent decades. In the present paper, one hundred journal articles published from 1999 to 2022 (i.e., the articles [11–110]) are surveyed and included in statistic. The annual distribution of these articles is depicted in Figure 1. As can be seen from the figure, there was a relatively slow increase in the number from 1999 to 2017, and the number has grown rapidly over the past five years. In addition, more than 80% of articles were published during the past ten years, which delineates the ongoing importance and popularity of the research topic.

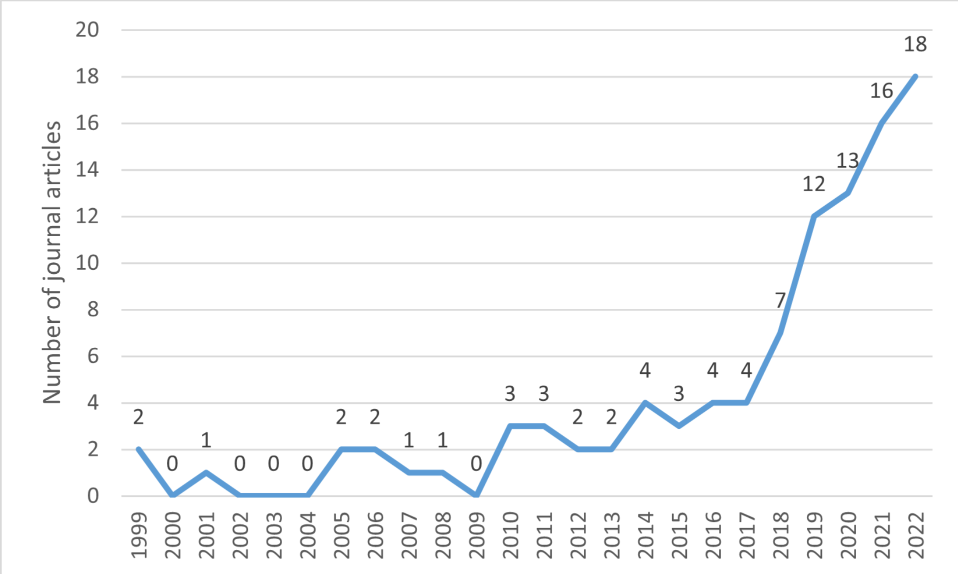

Figure 1. Annual distribution of the journal articles about MADM methods in AM.

From the perspective of the journals where the articles were published, the top five journals that have published the most research articles about MADM methods in AM include, as shown in Figure 2, Rapid Prototyping Journal (ISSN: 1355-2546), The International Journal of Advanced Manufacturing Technology (ISSN: 0268-3768), Materials Today: Proceedings (ISSN: 2214-7853), Robotics and Computer-Integrated Manufacturing (ISSN: 0736-5845), and Procedia CIRP (ISSN: 2212-8271). It can also be seen from the figure that the Rapid Prototyping Journal and The International Journal of Advanced Manufacturing Technology published a total of thirty-one articles, accounting for 31% of the articles included in the statistic.

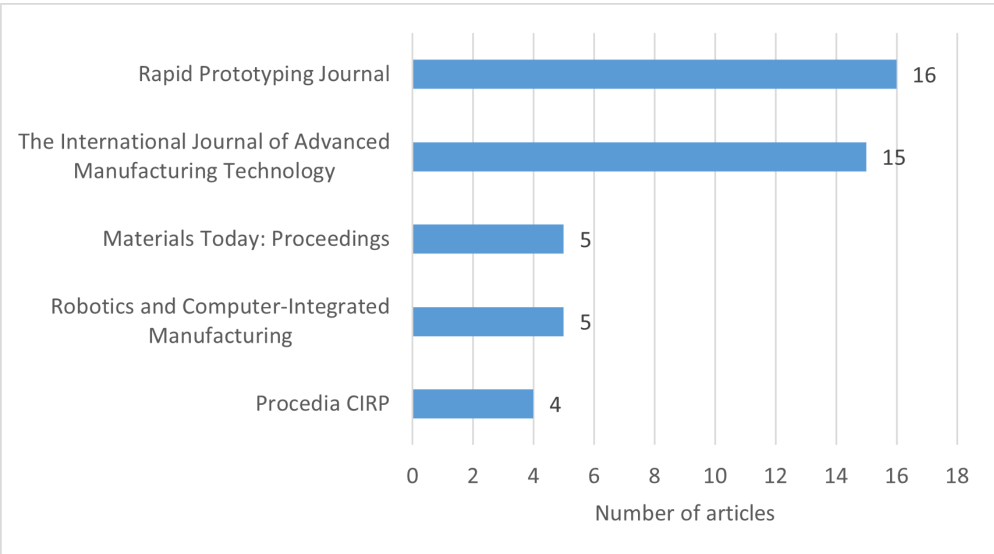

Figure 2. Top five journals that published the most articles about MADM methods in AM.

From the perspective of the citations of the published articles, the ten articles about MADM methods in AM with the greatest number of total citations are, as listed in Figure 3 (data source: Google Scholar, accessed on 23 November 2022), Chakraborty [62], Byun and Lee [78], Byun and Lee [13], Vahdani et al. [44], Ic [45], Roberson et al. [58], Rao and Padm [61], Rao and Patel [80], Pham et al. [11], and Byun and Lee [12]. If the evaluation criterion is the average number of citations per year, the top ten articles about MADM methods in AM are, as listed in Figure 4 (data source: Google Scholar, accessed on 23 November 2022), Chakraborty [62], Kamaal et al. [53], Uz Zaman et al. [35], Wang et al. [94], Ic [45], Knofius et al. [32], Vahdani et al. [44], Byun and Lee [78], Roberson et al. [58], and Ransikarbum et al. [42]. From the two figures, it can be found that the articles that meet both evaluation criteria include Chakraborty [62], Byun and Lee [78], Vahdani et al. [44], Ic [45], and Roberson et al. [58]. Therefore, a total of fifteen different highly cited articles are included in the figures. A brief summary of these articles are listed in Table 1. As can be seen from the table, the annual distribution of the highly cited articles since 2005 is basically even. The journal that published the most highly cited articles was The International Journal of Advanced Manufacturing Technology. The most used MADM methods were AOs, AHP, TOPSIS, and hybrid methods. The most studied problem is process selection.

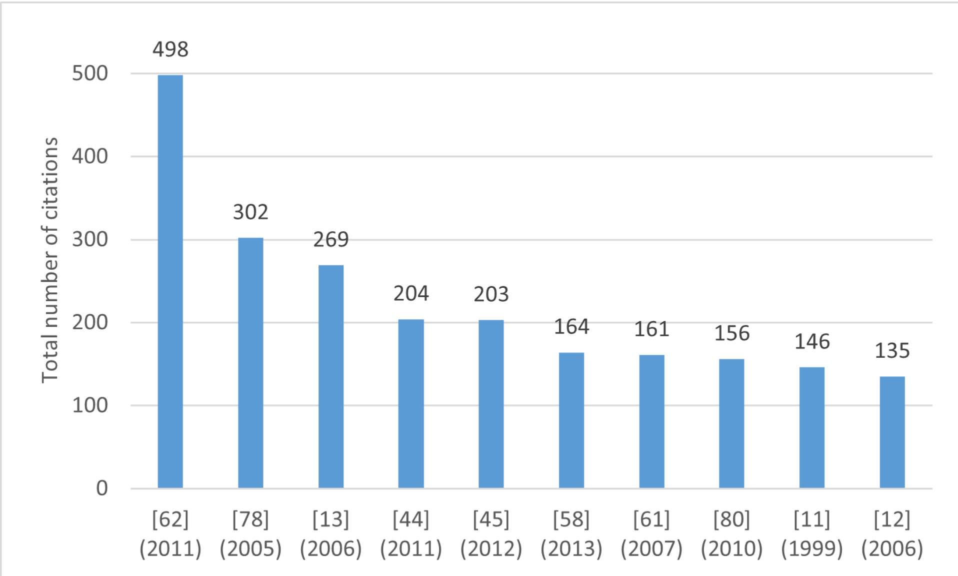

Figure 3. Top ten articles about MADM methods in AM based on total number of citations.

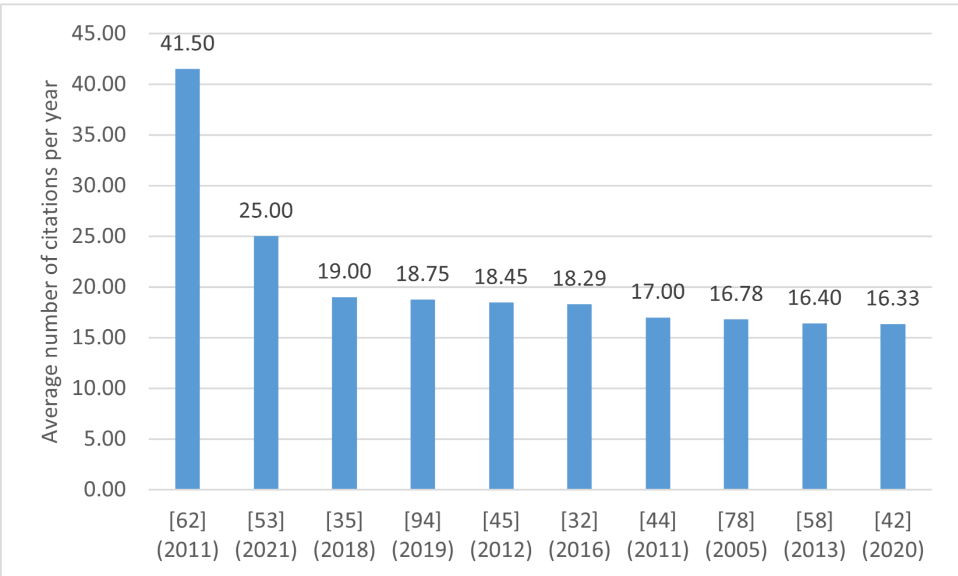

Figure 4. Top ten articles about MADM methods in AM based on average number of citations.

Table 1. Summary of the fifteen highly cited articles about MADM methods in AM.

Article	Year	Journal	Methods	Problems
Pham et al. [11]	1999	Int J Adv Manuf Technol	AO	Part orientation
Byun and Lee [78]	2005	Int J Adv Manuf Technol	Hybrid	Process selection
Byun and Lee [12]	2006	Int J Adv Manuf Technol	AO	Part orientation
Byun and Lee [13]	2006	Robot Comput-Integr Manuf	AO	Part orientation
Rao and Padm [61]	2007	J Mater Process Technol	GTMA	Process selection
Rao and Patel [80]	2010	Int J Prod Res	Hybrid	Process selection
Chakraborty [62]	2011	Int J Adv Manuf Technol	MOORA	Process selection
Vahdani et al. [44]	2011	Appl Math Model	TOPSIS	Process selection
Ic [45]	2012	Robot Comput-Integr Manuf	TOPSIS	Process selection
Roberson et al. [58]	2013	Virtual Phys Prototyp	DF	Process selection
Knofius et al. [32]	2016	J Manuf Technol Manag	AHP	Part selection
Uz Zaman et al. [35]	2018	Robot Comput-Integr Manuf	AHP	Multiple problems
Wang et al. [94]	2019	Int J Adv Manuf Technol	Hybrid	AM-related assessment
Ransikarbum et al. [42]	2020	Appl Sci	AHP	Production scheduling
Kamaal et al. [53]	2021	Prog Addit Manuf	TOPSIS	Parameter optimisation

3.2. Specific Methods Applied in AM

Based on the overview of MADM methods in AM, the classification of the MADM methods used is depicted in Figure 5. The methods used are divided into two categories. The first category consists of sixteen single methods. The second category contains twenty-five hybrid methods, each of which is obtained via integrating two or more single methods. According to the related literature, the main strengths and weaknesses of the methods used are summarised and listed in Table 2. As can be seen from the table, each method has its specific advantages and disadvantages. It is difficult to say which method is the best. In practical applications, the most suitable method for a problem should be selected according to the characteristics of the problem.

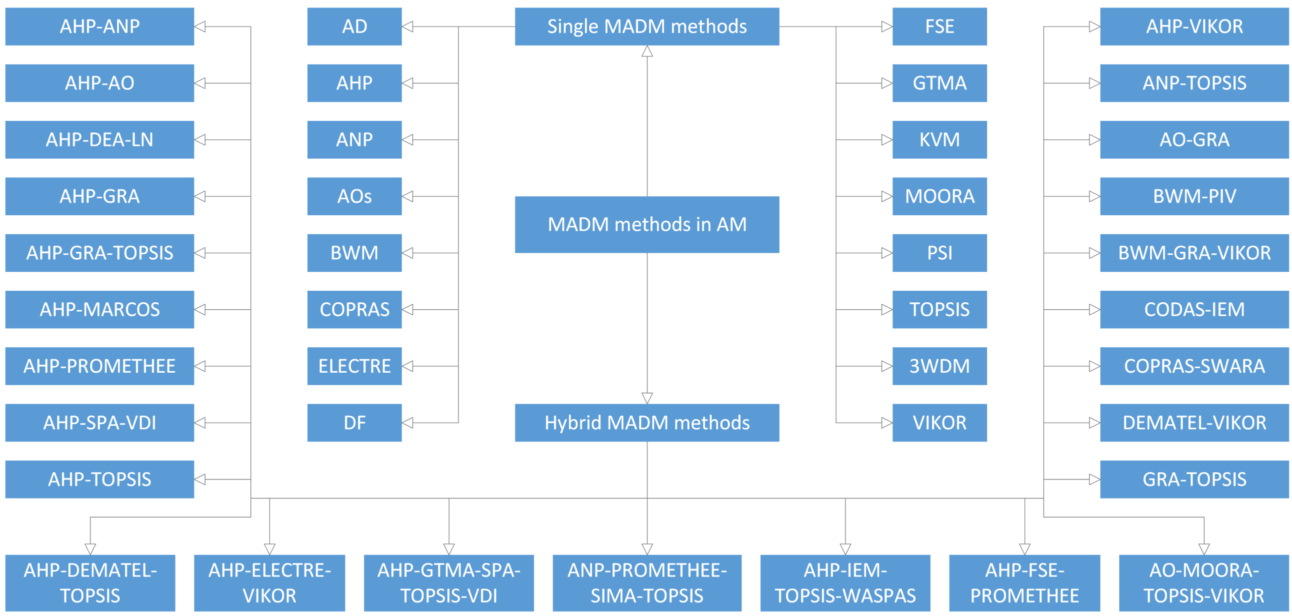

Figure 5. Classification of the MADM methods applied in AM.

Table 2. Summary of the main strengths and weaknesses of the MADM methods applied in AM.

Method	Main Strengths	Main Weaknesses
AD	Overcomes the subjectivity of interpretation, solves fundamental issues in Taguchi methods	A system design methodology, its robustness for MADM problems requires further validation
AHP	Good scalability, easy to use, not data-intensive, possible to measure the consistency of judgments	Not efficient for large-scale problems, not always a solution to the linear equations
ANP	Simplifies complex problems and supports dependence and feedback in hierarchy	Relies on judgment and experience of experts, large number of attributes may lead to unwieldy model
AOs	Easy to use, provide summary attribute values, each AO has its specific capability	Some AOs are very complicated and their computational cost is relatively high
BWM	More consistent pairwise comparisons, mitigates anchoring bias, flexible in group decision-making	Not producing a globally optimal solution, not conducive when the number of attributes is large
COPRAS	Not requiring transformation to minimise attributes, allowing to compare and check measuring results	Results may be sensitive to slight variations in the input data
ELECTRE	Considers the uncertainty and imprecision of the input data	The decision process and generation results can be difficult to explain
DF	Provides an effective way to quantify the trade-offs between attributes	Depends on the empirical data that are difficult to obtain in some problems
FSE	Provides an effective approach to describe vague, imprecise, and uncertain information	Depends on subjective judgement, and a large number of attributes could invalidate the model
GTMA	Simple, intuitive, and easy to understand and use, considers the interrelations of attributes	Effectiveness and robustness require further demonstration
KVM	Simplicity and efficiency of using structured expert knowledge or experience	The knowledge and experience are sometimes difficult to obtain
MOORA	Straightforward, efficient, robust, non-subjective, does not need external normalisation	Not efficient when the decision matrix contains a large number of attributes
PSI	Not needing the degrees of importance between attributes and the weights of attributes	Not considering relative importance of attributes when generating the ranking results
TOPSIS	Simple and efficient, the number of steps is not affected by the number of attributes	Subjective, difficult to keep consistency, not considering the correlation of attributes
3WDM	Prevents premature classification of the alternatives at the edge of acceptance and rejection	Needs decision costs and conditional probabilities that are sometimes difficult to determine as input
VIKOR	Can benefit the decision makers who are unstable or have no idea regarding expressing preferences	Needs different attribute weights and an analysis of the effect of weights on compromise solution
Hybrid	Can take advantage of the strengths of two or more single methods	Might be challenging to find the best combination of single methods

According to this overview, the distribution of the MADM methods used is obtained and depicted in Figure 6. It can be seen that hybrid methods are the most used methods. The reason may be that a hybrid method can take advantage of the strengths of two or more single methods. In addition to the hybrid methods, the more commonly used methods are AHP, TOPSIS, and AOs. This may be due to the simplicity and generality of these methods and their strong reputation in the field of MADM.

For the hybrid methods used, two statistics were made. The first one relates to the distribution of the hybrid methods, while the second one relates to the distribution of the single methods integrated into the hybrid methods. The results of the two statistics are depicted in Figure 7 and Figure 8, respectively. As shown in these two figures, the most used hybrid method is AHP-TOPSIS, and the single method with the highest frequency of integration in the hybrid methods is AHP, followed by TOPSIS. These results are consistent with those shown in Figure 6, which further illustrate that AHP and TOPSIS are the two most popular single methods for MADM problems in the field of AM.

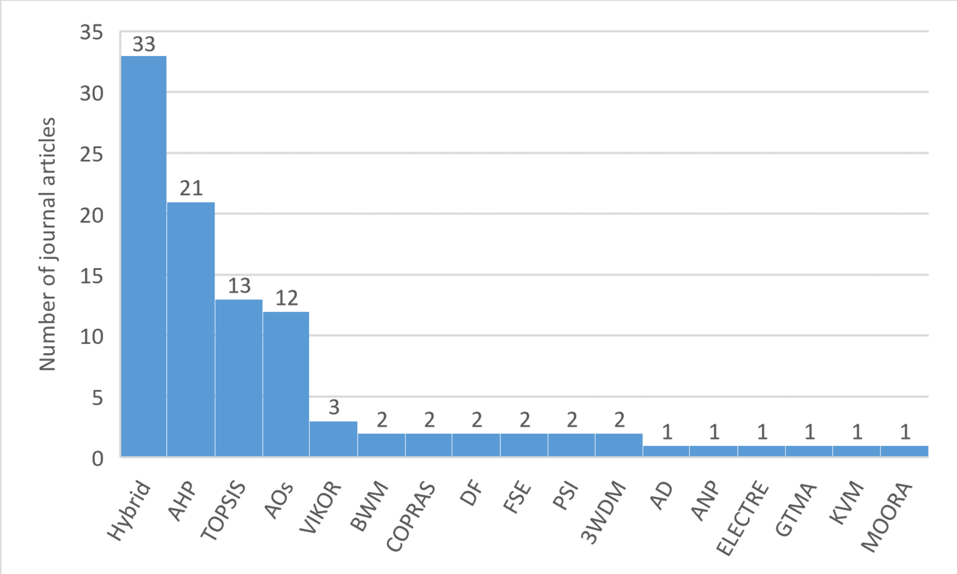

Figure 6. Distribution of the MADM methods applied in AM.

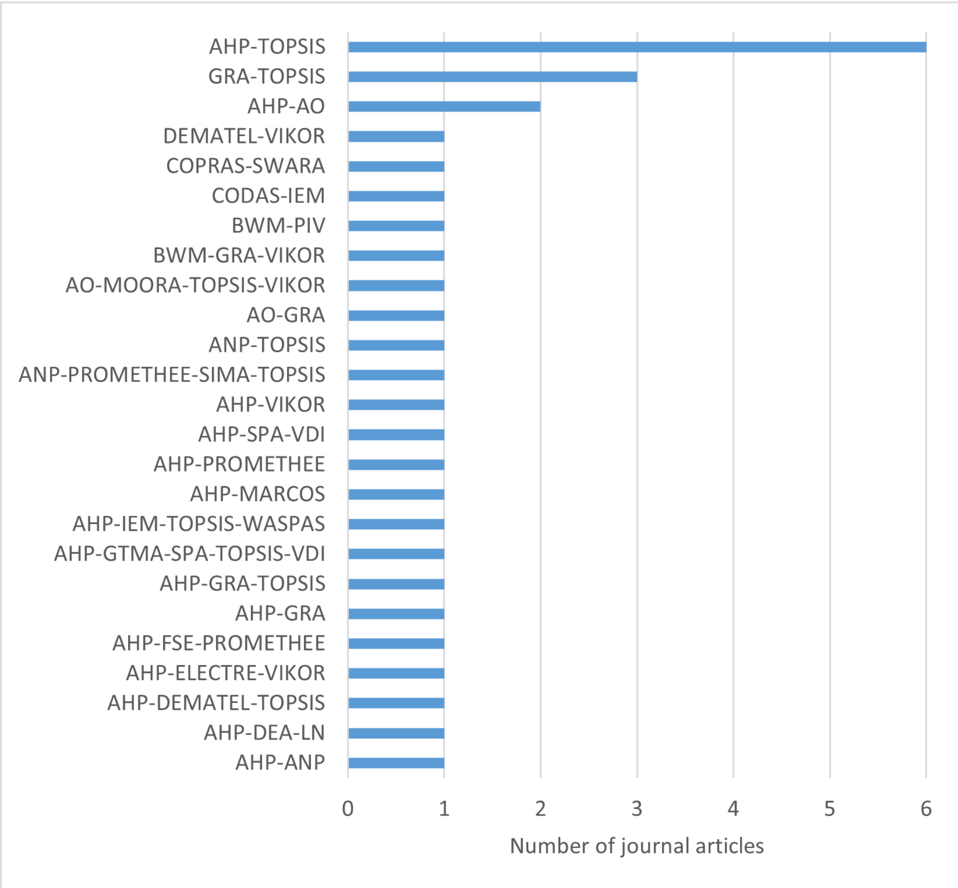

Figure 7. Distribution of the hybrid methods.

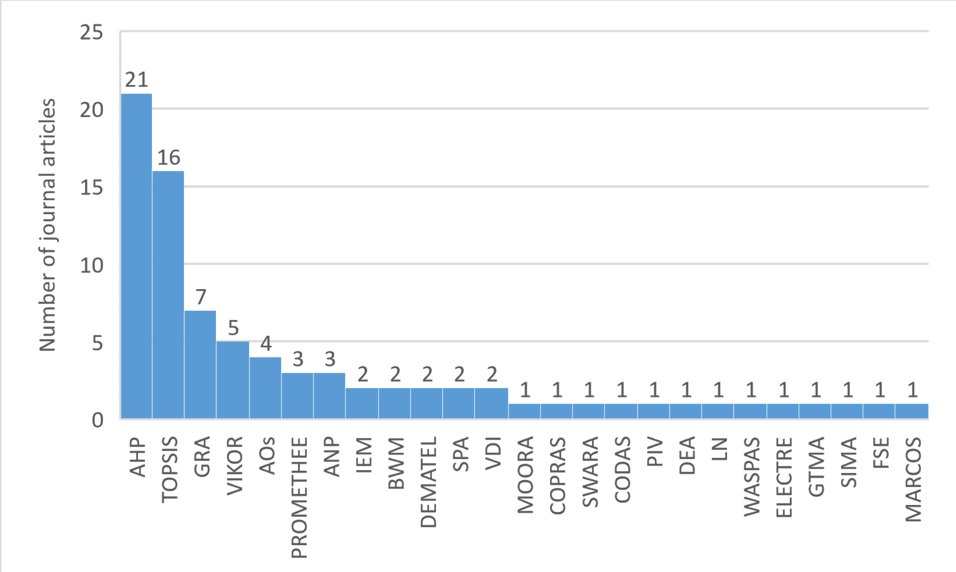

Figure 8. Distribution of the single methods integrated in the hybrid methods.

3.3. Problems Solved by the Methods

According to the overview of MADM methods in AM, there are a total of ten problems in AM that have been solved by MADM methods. These are process selection, AM-related assessment, part orientation, parameter optimisation, material selection, multiple problems, part selection, adhesive selection, design selection, and production scheduling. The distribution of the articles included in the overview with respect to the seventeen MADM methods in Figure 6 and these ten problems is listed in Table 3. It is obvious that process selection is the most popular problem tackled by MADM methods. This problem is followed by AM-related assessment, part orientation, parameter optimisation, material selection, and multiple problems, which have received roughly the same level of attention in the application of MADM methods. Compared to these six problems, the four remaining problems including part selection, adhesive selection, design selection, and production scheduling are least addressed by MADM methods.

Table 3. Distribution of the articles with respect to the applied MADM methods and the solved problems.

MADM Method	Process Selection	AM-Related Assessment	Part Orientation	Parameter Optimisation	Material Selection	Multiple Problems	Part Selection	Adhesive Selection	Design Selection	Production Scheduling
Hybrid	[78–81,84,85,87,89–93,95,99,104]	[82,88,94,102,110]	[86,98,100,109]	[101,105,108]	[96,97,106,107]	[83,103]				
AHP	[23–30]	[39–41]			[38]	[35–37]	[32–34]	[31]	[43]	[42]
TOPSIS	[44–46,49,50]	[48,51,52]	[47]	[53–55]	[56]					
AOs	[19–21]	[18]	[11–17]			[22]				
VIKOR	[64]			[65,66]						
BWM		[75]				[74]				
COPRAS	[67,68]									
DF	[58]					[57]				
FSE	[59,60]									
PSI	[73]			[72]						
3WDM	[76]				[77]					
AD	[70]									
ANP	[69]									
ELECTRE					[71]					
GTMA	[61]									
KVM	[63]									
MOORA	[62]									

4. Discussion of Main Issues

Based on the review of the state of the art, the main issues in the application of MADM methods to the field of AM that need to be solved in future studies can be discussed through the following aspects:

(1) Selection of an MADM method: There are already a large number of available MADM methods in the literature, but there is no guideline or standard to guide how to choose the most suitable method for a specific MADM problem in AM. In existing studies, many different methods are applied to solve the same problem. It is difficult to find the best method for a problem. Therefore, which method to choose usually depends on the knowledge and experience of a user. This places significant requirements on users.

(2) Generation of alternatives: In some MADM problems in AM, the alternatives are not directly available. They need to be obtained via certain approaches. In this case, the quality of the decision-making results depends not only on the MADM methods used, but also on the obtained alternatives. For example, to apply an MADM method to solve the part orientation problem, specific approaches such as feature recognition, convex hull generation, quaternion rotation, and facet clustering need to be used to generate a finite number of alternative orientations first, and then the best orientation can be selected from them using the MADM method. It is not difficult to understand that the quality of the selected orientation is affected by both the generated alternative orientations and the applied MADM method.

(3) Consideration of attributes: For the same MADM problem in AM, different studies may consider different attributes in their decision-making process. This can be very confusing, since there is not a guideline or standard that recommends which attributes each problem should consider.

(4) The determination of the weights of attributes: The weights of attributes quantify their relative importance in producing the decision-making results. A slight variation in the weights could significantly affect the decision-making results. In most studies, the weights of attributes are directly assigned. Generally, it is difficult to assign proper attribute weights, since this needs prior knowledge of how the attributes affect the decision-making results. Furthermore, the considered attributes are usually conflicting or interrelated, which makes the task more complicated. A few studies calculate the attribute weights based on the degrees of importance of the attributes evaluated by domain experts. This way seems more convincing, but it is still highly subjective.

(5) The acquisition of measures of performance: In some MADM problems in AM, the measures of performance of the alternatives with respect to the attributes can only be acquired via the evaluation of domain experts or the prediction of analytical models. The main limitation of the first approach lies in its high degree of subjectivity. For the second approach, it is not easy to build accurate analytical models.

(6) Demonstration of effectiveness: Effectiveness is the most important criterion to evaluate an MADM method in AM. However, a common problem for MADM methods is that demonstrating the effectiveness of a method is usually difficult, as the best ranking for an MADM problem is unknown. In the literature, some studies just illustrate the process of using certain MADM methods to solve AM problems via numerical examples, while others compare the ranking results produced by one method to that generated by several other similar methods. Strictly speaking, neither way is sufficient to verify the effectiveness of the methods used.

(7) Demonstration of efficiency: Efficiency is another important criterion to evaluate an MADM method in AM, especially when the method is applied to large-scale MADM problems in AM. However, this criterion is not considered in most current studies. This may be because the number of alternatives in most MADM problems in AM is not large. However, there are a few problems (e.g., part orientation, parameter optimisation, part selection) where the number of alternatives could be huge, for which it would be of necessity to consider the efficiency of the applied MADM methods.

(8) Integrated MADM: In most existing studies, MADM problems in AM product realisation activities are tackled in an isolate manner. This requires repeated trial and error to realise the performance of an AM product, since the problems in different activities are usually interrelated. To cope with this challenge, an integrated MADM methodology is needed to enable the concurrent design of the material, structure, and process and emphasise their mutual compatibility. However, the existing studies have not developed such a methodology.
(9) Standardisation of the solving process of MADM problems in AM: The standardisation of the MADM process for problems in AM is the basis for realising practical application. However, for the current MADM problems in AM, there is not a problem whose solving process has been standardised.
(10) Integration of MADM methods with commercial software systems: The integration of MADM methods with commercial software systems for AM can greatly facilitate the application of the methods in AM. However, it is unclear how many MADM methods have been implemented in commercial software systems for AM because there is little evidence.

5. Conclusions

In this paper, the recently established applications of MADM methods in the field of AM are reviewed, analysed, and discussed. It can be observed that this research topic has been of continuing importance and popularity during the past five years. The Rapid Prototyping Journal and The International Journal of Advanced Manufacturing Technology published the most articles on the research topic. Regardless of the total number of citations or the average number of citations per year, the most cited article is that by Chakraborty [62], in which the application of MOORA for MADM in manufacturing environment is studied. The MADM methods that have been applied to the field of AM include hybrid methods, AHP, TOPSIS, AOs, VIKOR, BWM, COPRAS, DF, FSE, PSI, 3WDM, AD, ANP, ELECTRE, GTMA, KVM, and MOORA, where the first four methods are the most used. Each method has its specific strengths and weaknesses. It is difficult to say which method is the best. In practical applications, the most suitable method for a specific problem in AM should be selected based on the characteristics of the problem. It is also found that the problems in AM that have been solved by MADM methods include process selection, AM-related assessment, part orientation, parameter optimisation, material selection, multiple problems, part selection, adhesive selection, design selection, and production scheduling, where the first problem is the most studied.

Although MADM methods have been successfully applied to the field of AM, there are still a number of issues in these applications that need to be addressed in future studies. The main issues lie in the difficulties in choosing the most suitable method for a specific problem, obtaining the alternatives, selecting the attributes, determining the weights of attributes, acquiring the values of attributes, and demonstrating their effectiveness. In addition, the demonstration of the efficiency, the development of an integrated MADM methodology, the standardisation of the solving process of MADM problems in AM, and the integration of MADM methods with commercial software systems for AM have not been well addressed to date.

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List of Acronyms

AD	Axiomatic Design
AHP	Analytical Hierarchy Process
AM	Additive Manufacturing
ANP	Analytical Network Process
AO	Aggregation Operator
BWM	Best–Worst Method
CODAS	Combinative Distance-based Assessment
COPRAS	Complex Proportional Assessment
DEA	Data Envelopment Analysis
DEMATEL	Decision Making Trial and Evaluation Laboratory
DF	Deviation Function
ELECTRE	Elimination Et Choix Traduisant la Réalité
FDM	Fused Deposition Modelling
FSE	Fuzzy Synthetic Evaluation
GRA	Grey Relational Analysis
GTMA	Graph Theory and Matrix Approach
IEM	Information Entropy Method
KVM	Knowledge Value Measuring
LN	Linear Normalisation
MADM	Multi-Attribute Decision-Making
MARCOS	Measurement Alternatives and Ranking According to Compromise Solution
MOORA	Multi-Objective Optimisation by Ratio Analysis
PIV	Proximity Indexed Value
PSI	Preference Selection Index
PROMETHEE	Preference Ranking Organisation Method for Enrichment Evaluation
SIMA	Similarity-based Approach
SLA	Stereolithography
SLM	Selective Laser Melting
SLS	Selective Laser Sintering
SPA	Simple Pair Analysis
SWARA	Stepwise Weight Assessment Ratio Analysis
3D	Three-Dimensional
3WDM	Three-Way Decision Model
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
VDI	Verein Deutscher Ingenieure
VIKOR	Vlsekriterijuska optimizacija I Komoromisno Resenje
WASPAS	Weighted Aggregated Sum Product Assessment

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