Multi-Attribute Decision-Making Methods in Additive Manufacturing

Subjects: Engineering, Manufacturing
Contributor: Yuchu Qin, Qunfen Qi, Peizhi Shi, Shan Lou, Paul J. Scott, Xiangqian Jiang

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.

Keywords: additive manufacturing ; decision problem ; optimisation

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][4][5].

2. MADM Methods in AM

2.1. AOs in AM

Aggregation operators (AOs), also known as aggregation functions, are mathematical functions for grouping together multiple values to obtain a single summary value [6]. 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 additive manufacturing (AM), AOs have been applied to tackle the problems below.

2.1.1. AOs in Part Orientation

Pham et al. [7] 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 [8][9] 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 three-dimensional (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. [10] 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.

2.1.2. AOs in AM-Related Assessment

Moreno-Cabezali and Fernandez-Crehuet [11] 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. [12] 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. [13] 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. [14] 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 [13], this AO can also capture the interrelationships among multiple attributes.

2.1.4. AOs in Multiple Problems

Huang et al. [15] 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 [14], the developed approach also has the capability to capture the risk attitudes of decision makers.

2.2. AHP in AM

Analytical hierarchy process (AHP) is a structured MADM method based on mathematics and psychology for organising and analysing complex decisions [16]. 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 [17] 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 [18] 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 [19] 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.

2.2.2. AHP in Adhesive Selection

Arenas et al. [20] 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. [21] 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. [22] 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. [23] 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. [24] 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. [25] 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. [26] 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. [27] 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. [28] 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. [29] 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. [30] 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. [31] 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. [32] 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

Technique for order of preference by similarity to an ideal solution (TOPSIS) is an MADM method that ranks the alternatives according to their geometric distances from the best solution and from the worst solution [33]. 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. [34] 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 [35] 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 [36] 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.

2.3.2. TOPSIS in Part Orientation

Yu et al. [37] 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. [38] 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 [39] 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 [40] 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. [41] 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. [42] 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. [43] 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. [44] 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 deviation function (DF) [45], fuzzy synthetic evaluation (FSE) [46], graph theory and matrix approach (GTMA) [47], multi-objective optimisation by ratio analysis (MOORA) [48], knowledge value measuring (KVM) [49], vlsekriterijuska optimizacija i komoromisno resenje (VIKOR) [50], complex proportional assessment (COPRAS) [51], analytical network process (ANP) [52], axiomatic design (AD [53], elimination et choix traduisant la réalité (ELECTRE) [54], preference selection index (PSI) [55], best–worst method (BWM) [56], and three-way decision model (3WDM) [57], 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. [58] 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. [59] 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. [60] 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. [63], 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. [64], 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. [65], 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.

2.4.3. Other Single Methods in Parameter Optimisation

Patel et al. [66] 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 [67] 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 [68] 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. [69] 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. [70] 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 [71] 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

2.5.1. Hybrid Methods in Process Selection

Byun and Lee [72] 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. [73] 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 [74] 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 [75], 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. [76], 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. [77], 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.

2.5.2. Hybrid Methods in AM-Related Assessment

Liao et al. [78] 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 [79] 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. [80] 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. [81], 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. [82], 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 [84] 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. [85] 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. [86] 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. [87] 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.

2.5.5. Hybrid Methods in Material Selection

Zhang et al. [88] 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 [89] 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. [90] 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. [91], 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 [92] 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. [93] 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. [94] 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.

References

1. Tzeng, G.H.; Huang, J.J. Multiple Attribute Decision Making: Methods and Applications; CRC Press: Boca Raton, FL, USA, 2011.
2. Churchman, C.W.; Ackoff, R.L.; Arnoff, E.L. Introduction to Operations Research; Wiley: Hoboken, NJ, USA, 1957.
3. Velasquez, M.; Hester, P.T. An analysis of multi-criteria decision making methods. Int. J. Oper. Res. 2013, 10, 56–66.
4. Aruldoss, M.; Lakshmi, T.M.; Venkatesan, V.P. A Survey on Multi Criteria Decision Making Methods and Its Applications. Am. J. Inf. Syst. 2013, 1, 31–43.
5. Zavadskas, E.K.; Turskis, Z.; Kildiene, S. State of art surveys of overviews on MCDM/MADM methods. Technol. Econ. Dev. Econ. 2014, 20, 165–179.
6. Beliakov, G.; Pradera, A.; Calvo, T. Aggregation Functions: A Guide for Practitioners; Springer: Berlin, Germany, 2007.
7. Pham, D.T.; Dimov, S.S.; Gault, R.S. Part orientation in stereolithography. Int. J. Adv. Manuf. Technol. 1999, 15, 674–682.

8. Byun, H.S.; Lee, K.H. Determination of optimal build direction in rapid prototyping with variable slicing. Int. J. Adv. Manuf. Technol. 2006, 28, 307–313.
9. Byun, H.S.; Lee, K.H. Determination of the optimal build direction for different rapid prototyping processes using multi-criterion decision making. Robot. Comput.-Integr. Manuf. 2006, 22, 69–80.
10. Al-Ahmari, A.M.; Abdulhameed, O.; Khan, A.A. An automatic and optimal selection of parts orientation in additive manufacturing. Rapid Prototyp. J. 2018, 24, 698–708.
11. Moreno-Cabezali, B.M.; Fernandez-Crehuet, J.M. Application of a fuzzy-logic based model for risk assessment in additive manufacturing R&D projects. Comput. Ind. Eng. 2020, 145, 106529.
12. Qin, Y.; Qi, Q.; Scott, P.J.; Jiang, X. An additive manufacturing process selection approach based on fuzzy Archimedean weighted power Bonferroni aggregation operators. Robot. Comput.-Integr. Manuf. 2020, 64, 101926.
13. Qin, Y.; Qi, Q.; Shi, P.; Scott, P.J.; Jiang, X. Linguistic interval-valued intuitionistic fuzzy Archimedean prioritised aggregation operators for multi-criteria decision making. J. Intell. Fuzzy Syst. 2020, 38, 4643–4666.
14. Qin, Y.; Cui, X.; Huang, M.; Zhong, Y.; Tang, Z.; Shi, P. Linguistic Interval-Valued Intuitionistic Fuzzy Archimedean Power Muirhead Mean Operators for Multi-Attribute Group Decision Making. Complexity 2020, 2020, 2373762.
15. Huang, M.; Chen, L.; Zhong, Y.; Qin, Y. A generic method for multi-criterion decision-making problems in design for additive manufacturing. Int. J. Adv. Manuf. Technol. 2021, 115, 2083–2095.
16. Saaty, T.L. How to make a decision: The analytic hierarchy process. Eur. J. Oper. Res. 1990, 48, 9–26.
17. Braglia, M.; Petroni, A. A management-support technique for the selection of rapid prototyping technologies. J. Ind. Technol. 1999, 15, 2–6.
18. Armillotta, A. Selection of layered manufacturing techniques by an adaptive AHP decision model. Robot. Comput.-Integr. Manuf. 2008, 24, 450–461.
19. Lokesh, K.; Jain, P.K. Selection of rapid prototyping technology. Adv. Prod. Eng. Manag. 2010, 5, 75–84.
20. Arenas, J.M.; Alia, C.; Blaya, F.; Sanz, A. Multi-criteria selection of structural adhesives to bond ABS parts obtained by rapid prototyping. Int. J. Adhes. Adhes. 2012, 33, 67–74.
21. Knofius, N.; Van der Heijden, M.C.; Zijm, W.H.M. Selecting parts for additive manufacturing in service logistics. J. Manuf. Technol. Manag. 2016, 27, 915–931.
22. Muvunzi, R.; Mpofu, K.; Daniyan, I. An Evaluation Model for Selecting Part Candidates for Additive Manufacturing in the Transport Sector. Metals 2021, 11, 765.
23. Foshammer, J.; Soberg, P.V.; Helo, P.; Ituarte, I.F. Identification of aftermarket and legacy parts suitable for additive manufacturing: A knowledge management-based approach. Int. J. Prod. Econ. 2022, 253, 108573.
24. Uz Zaman, U.K.; Rivette, M.; Siadat, A.; Mousavi, S.M. Integrated product-process design: Material and manufacturing process selection for additive manufacturing using multi-criteria decision making. Robot. Comput.-Integr. Manuf. 2018, 51, 169–180.
25. Hodonou, C.; Balazinski, M.; Brochu, M.; Mascle, C. Material-design-process selection methodology for aircraft structural components: Application to additive vs. subtractive manufacturing processes. Int. J. Adv. Manuf. Technol. 2019, 103, 1509–1517.
26. Kadkhoda-Ahmadi, S.; Hassan, A.; Asadollahi-Yazdi, E. Process and resource selection methodology in design for additive manufacturing. Int. J. Adv. Manuf. Technol. 2019, 104, 2013–2029.
27. Alghamdy, M.; Ahmad, R.; Alsayyed, B. Material selection methodology for additive manufacturing applications. Procedia CIRP 2019, 84, 486–490.
28. Foteinopoulos, P.; Papacharalampopoulos, A.; Stavropoulos, P. Block-based analytical hierarchy process applied for the evaluation of construction sector additive manufacturing. Procedia CIRP 2019, 81, 950–955.
29. Sonar, H.C.; Khanzode, V.V.; Akarte, M.M. Ranking of additive manufacturing implementation factors using analytic hierarchy process (AHP). J. Inst. Eng. Ser. C 2021, 102, 421–426.
30. Bappy, M.M.; Key, J.; Hossain, N.U.I.; Jaradat, R. Assessing the Social Impacts of Additive Manufacturing Using Hierarchical Evidential Reasoning Approach. Glob. J. Flex. Syst. Manag. 2022, 23, 201–220.
31. Ransikarbum, K.; Pitakaso, R.; Kim, N. A decision-support model for additive manufacturing scheduling using an integrative analytic hierarchy process and multi-objective optimization. Appl. Sci. 2020, 10, 5159.
32. Rochman, D.D.; Anwar, A.; Riki Margana, R. 3D Print COVID-19 Mask Design Selection using Analytical Hierarchy Process. Solid State Technol. 2020, 63, 3127–3136.

33. Hwang, C.L.; Yoon, K. Multiple Attribute Decision Making: Methods and Applications A State-of-the-Art Survey; Springer: Berlin, Germany, 1981.

34. Vahdani, B.; Mousavi, S.M.; Tavakkoli-Moghaddam, R. Group decision making based on novel fuzzy modified TOPSIS method. Appl. Math. Model. 2011, 35, 4257–4269.

35. Ic, Y.T. An experimental design approach using TOPSIS method for the selection of computer-integrated manufacturing technologies. Robot. Comput.-Integr. Manuf. 2012, 28, 245–256.

36. Yildiz, A.; Ugur, L. Evaluation of 3D printers used in additive manufacturing by using interval type-2 fuzzy TOPSIS method. J. Eng. Res. Appl. Sci. 2018, 7, 984–993.

37. Yu, C.; Qie, L.; Jing, S.; Yan, Y. Personalized design of part orientation in additive manufacturing. Rapid Prototyp. J. 2019, 25, 1647–1660.

38. Priarone, P.C.; Pagone, E.; Martina, F.; Catalano, A.R.; Settineri, L. Multi-criteria environmental and economic impact assessment of wire arc additive manufacturing. CIRP Ann. 2020, 69, 37–40.

39. Alsaadi, N. Prioritization of Challenges for the Effectuation of Sustainable Additive Manufacturing: A Case Study Approach. Processes 2021, 9, 2250.

40. Agrawal, R. Sustainable design guidelines for additive manufacturing applications. Rapid Prototyp. J. 2022, 28, 1221–1240.

41. Kamaal, M.; Anas, M.; Rastogi, H.; Bhardwaj, N.; Rahaman, A. Effect of FDM process parameters on mechanical properties of 3D-printed carbon fibre–PLA composite. Prog. Addit. Manuf. 2021, 6, 63–69.

42. Sugavaneswaran, M.; Prashanthi, B.; Rajan, J. A multi-criteria decision making method for vapor smoothening fused deposition modelling part. Rapid Prototyp. J. 2021, 28, 236–252.

43. Kumar, S.; Singh, R.; Singh, T.P.; Batish, A. On twin screw extrusion parametric optimisation using hybrid approach of ANOVA and TOPSIS for 3D printing applications. Adv. Mater. Process. Technol. 2022.

44. Jha, M.K.; Gupta, S.; Chaudhary, V.; Gupta, P. Material selection for biomedical application in additive manufacturing using TOPSIS approach. Mater. Today Proc. 2022, 62, 1452–1457.

45. Schervish, M.J. Theory of Statistics; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2012.

46. Zadeh, L.A. Fuzzy sets. Inf. Control 1965, 8, 338–353.

47. Rao, R.V. A material selection model using graph theory and matrix approach. Mater. Sci. Eng. A 2006, 431, 248–255.

48. Brauers, W.K.; Zavadskas, E.K. The MOORA method and its application to privatization in a transition economy. Control Cybern. 2006, 35, 445–469.

49. Lee, C.C.; Yang, J. Knowledge value chain. J. Manag. Dev. 2000, 19, 783–794.

50. Duckstein, L.; Opricovic, S. Multiobjective optimization in river basin development. Water Resour. Res. 1980, 16, 14–20.

51. Zavadskas, E.K.; Kaklauskas, A.; Peldschus, F.; Turskis, Z. Multi-attribute assessment of road design solutions by using the COPRAS method. Balt. J. Road Bridge Eng. 2007, 2, 195–203.

52. Saaty, T.L. Decision Making with Dependence and Feedback: The Analytic Network Process; RWS Publications: Pittsburgh, PA, USA, 1996.

53. Suh, N.P.; Suh, N.P. Axiomatic Design: Advances and Applications; Oxford University Press: Oxford, UK, 2001.

54. Figueira, J.R.; Mousseau, V.; Roy, B. ELECTRE Methods. In Multiple Criteria Decision Analysis; Springer: Berlin/Heidelberg, Germany, 2016; pp. 155–185.

55. Maniya, K.; Bhatt, M.G. A selection of material using a novel type decision-making method: Preference selection index method. Mater. Des. 2010, 31, 1785–1789.

56. Rezaei, J. Best-worst multi-criteria decision-making method. Omega 2015, 53, 49–57.

57. Yao, Y. Three-way decisions with probabilistic rough sets. Inf. Sci. 2010, 180, 341–353.

58. West, A.P.; Sambu, S.P.; Rosen, D.W. A process planning method for improving build performance in stereolithography. Comput.-Aided Des. 2001, 33, 65–79.

59. Palanisamy, M.; Pugalendhi, A.; Ranganathan, R. Selection of suitable additive manufacturing machine and materials through best–worst method (BWM). Int. J. Adv. Manuf. Technol. 2020, 107, 2345–2362.

60. Lan, H.; Ding, Y.; Hong, J. Decision support system for rapid prototyping process selection through integration of fuzzy synthetic evaluation and an expert system. Int. J. Prod. Res. 2005, 43, 169–194.

61. Rao, R.V.; Padm, K.K. Rapid prototyping process selection using graph theory and matrix approach. J. Mater. Process. Technol. 2007, 194, 81–88.

62. Chakraborty, S. Applications of the MOORA method for decision making in manufacturing environment. Int. J. Adv. Manuf. Technol. 2011, 54, 1155–1166.

63. Khrais, S.; Al-Hawari, T.; Al-Araidah, O. A fuzzy logic application for selecting layered manufacturing techniques. Expert Syst. Appl. 2011, 38, 10286–10291.

64. Roberson, D.A.; Espalin, D.; Wicker, R.B. 3D printer selection: A decision-making evaluation and ranking model. Virtual Phys. Prototyp. 2013, 8, 201–212.

65. Vinodh, S.; Nagaraj, S.; Girubha, J. Application of fuzzy VIKOR for selection of rapid prototyping technologies in an agile environment. Rapid Prototyp. J. 2014, 20, 523–532.

66. Patel, P.B.; Patel, J.D.; Maniya, K.D. Application of PSI methods to select FDM process parameter for polylactic acid. Mater. Today Proc. 2018, 5, 4022–4028.

67. Raykar, S.J.; D'Addona, D.M. Selection of best printing parameters of fused deposition modeling using VIKOR. Mater. Today Proc. 2020, 27, 344–347.

68. Deomore, S.A.; Raykar, S.J. Multi-criteria decision making paradigm for selection of best printing parameters of fused deposition modeling. Mater. Today Proc. 2021, 44, 2562–2565.

69. Exconde, M.K.J.E.; Co, J.A.A.; Manapat, J.Z.; Magdaluyo, E.R., Jr. Materials selection of 3D printing filament and utilization of recycled polyethylene terephthalate (PET) in a redesigned breadboard. Procedia CIRP 2019, 84, 28–32.

70. Qin, Y.; Qi, Q.; Shi, P.; Scott, P.J.; Jiang, X. Selection of materials in metal additive manufacturing via three-way decision-making. Int. J. Adv. Manuf. Technol. 2023.

71. Agrawal, R.; Vinodh, S. Prioritisation of drivers of sustainable additive manufacturing using best worst method. Int. J. Sustain. Eng. 2021, 14, 1587–1603.

72. Byun, H.S.; Lee, K.H. A decision support system for the selection of a rapid prototyping process using the modified TOPSIS method. Int. J. Adv. Manuf. Technol. 2005, 26, 1338–1347.

73. Borille, A.; Gomes, J.; Meyer, R.; Grote, K. Applying decision methods to select rapid prototyping technologies. Rapid Prototyp. J. 2010, 16, 50–62.

74. Rao, R.V.; Patel, B.K. Decision making in the manufacturing environment using an improved PROMETHEE method. Int. J. Prod. Res. 2010, 48, 4665–4682.

75. Mahapatra, S.S.; Panda, B.N. Benchmarking of rapid prototyping systems using grey relational analysis. Int. J. Serv. Oper. Manag. 2013, 16, 460–477.

76. Paul, D.; Agarwal, P.; Mondal, G.; Banerjee, D. A comparative analysis of different hybrid MCDM techniques considering a case of selection of 3D printers. Manag. Sci. Lett. 2015, 5, 695–708.

77. Vimal, K.E.K.; Vinodh, S.; Brajesh, P.; Muralidharan, R. Rapid prototyping process selection using multi criteria decision making considering environmental criteria and its decision support system. Rapid Prototyp. J. 2016, 22, 225–250.

78. Liao, S.; Wu, M.J.; Huang, C.Y.; Kao, Y.S.; Lee, T.H. Evaluating and enhancing three-dimensional printing service providers for rapid prototyping using the DEMATEL based network process and VIKOR. Math. Probl. Eng. 2014, 2014, 349348.

79. Cruz, M.F.; Borille, A.V. Decision methods application to compare conventional manufacturing process with metal additive manufacturing process in the aerospace industry. J. Braz. Soc. Mech. Sci. Eng. 2017, 39, 177–193.

80. Wang, Y.C.; Chen, T.; Yeh, Y.L. Advanced 3D printing technologies for the aircraft industry: A fuzzy systematic approach for assessing the critical factors. Int. J. Adv. Manuf. Technol. 2019, 105, 4059–4069.

81. Zhang, C.; Zhang, C.; Zhuang, J.; Han, H.; Yuan, B.; Liu, J.; Yang, K.; Zhuang, S.; Li, R. Evaluation of Cloud 3D Printing Order Task Execution Based on the AHP-TOPSIS Optimal Set Algorithm and the Baldwin Effect. Micromachines 2021, 12, 801.

82. Yoris-Nobile, A.I.; Lizasoain-Arteaga, E.; Slebi-Acevedo, C.J.; Blanco-Fernandez, E.; Alonso-Canon, S.; Indacoechea-Vega, I.; Castro-Fresno, D. Life cycle assessment (LCA) and multi-criteria decision-making (MCDM) analysis to determine the performance of 3D printed cement mortars and geopolymers. J. Sustain. Cem.-Based Mater. 2022.

83. Zhang, Y.; Bernard, A. An integrated decision-making model for multi-attributes decision-making (MADM) problems in additive manufacturing process planning. Rapid Prototyp. J. 2014, 20, 377–389.

84. Algunaid, K.M.A.; Liu, J. Decision support system to select a 3D printing process/machine and material from a large-scale options pool. Int. J. Adv. Manuf. Technol. 2022, 121, 7643–7659.

85. Zhang, Y.; Bernard, A.; Gupta, R.K.; Harik, R. Feature based building orientation optimization for additive manufacturing. Rapid Prototyp. J. 2016, 22, 358–376.

86. Qin, Y.; Qi, Q.; Shi, P.; Scott, P.J.; Jiang, X. Automatic determination of part build orientation for laser powder bed fusion. Virtual Phys. Prototyp. 2021, 16, 29–49.

87. Ransikarbum, K.; Pitakaso, R.; Kim, N.; Ma, J. Multicriteria decision analysis framework for part orientation analysis in additive manufacturing. J. Comput. Des. Eng. 2021, 8, 1141–1157.

88. Zhang, H.; Wu, Y.; Wang, K.; Peng, Y.; Wang, D.; Yao, S.; Wang, J. Materials selection of 3D-printed continuous carbon fiber reinforced composites considering multiple criteria. Mater. Des. 2020, 196, 109140.

89. Agrawal, R. Sustainable material selection for additive manufacturing technologies: A critical analysis of rank reversal approach. J. Clean. Prod. 2021, 296, 126500.

90. Malaga, A.K.; Agrawal, R.; Wankhede, V.A. Material selection for metal additive manufacturing process. Mater. Today Proc. 2022, 66, 1744–1749.

91. Mastura, M.; Nadlene, R.; Jumaidin, R.; Kudus, S.A.; Mansor, M.; Firdaus, H. Concurrent Material Selection of Natural Fibre Filament for Fused Deposition Modeling Using Integration of Analytic Hierarchy Process/Analytic Network Process. J. Renew. Mater. 2022, 10, 1221.

92. Sakthivel, M.R.; Vinodh, S. Parametric optimization of fused deposition modelling process using Grey based Taguchi and TOPSIS methods for an automotive component. Rapid Prototyp. J. 2021, 27, 155–175.

93. Koli, Y.; Arora, S.; Ahmad, S.; Yuvaraj, N.; Khan, Z.A. Investigations and Multi-response Optimization of Wire Arc Additive Manufacturing Cold Metal Transfer Process Parameters for Fabrication of SS308L Samples. J. Mater. Eng. Perform. 2022.

94. Patil, P.; Singh, D.; Raykar, S.J.; Bhamu, J. Multi-objective optimisation and analysis of fused deposition modelling parameters: Best infill patterns. Int. J. Six Sigma Compet. Advant. 2022, 14, 18–31.