Selection of 3D printer for racing car spoilers using Entropy - CRADIS model

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Abstract:

Introduction/purpose: This study aims to identify the most suitable 3D printer for manufacturing racing car spoilers.

Methods: Sixteen different 3D printing machines are evaluated based on eight selection criteria including print volume, maximum print speed, layer thickness, number of extruders, machine cost, manufacturer filament price, maximum extruder temperature, and maximum bed temperature. The criteria weights are determined using the Entropy method, while the Compromise Ranking of Alternatives from Distance to Ideal Solution (CRADIS) method is applied to rank the machines and identify the best option for spoiler production. Sensitivity analysis is conducted using various methods to validate the results.

Results: Ultimaker 2 is identified as the most suitable 3D printer, followed by Delta Non-Turbo WASP 2040, while UP Plus 2 ranks as the least favorable.

Conclusion: By using the Entropy and CRADIS methods, Ultimaker 2 is identified as the best-performing 3D printer, followed by Delta Non-Turbo WASP 2040, while UP Plus 2 is ranked the lowest. Various MCDM methods are applied for performance comparison and sensitivity analysis, with the Spearman Rank Correlation Coefficient applied to assess the correlation between different MCDM methods.

Key words: additive manufacturing, 3D Printing, multi-criteria decision making, entropy, CRADIS, densitivity analysis.

Introduction

3D printing, also known as additive manufacturing, is a cutting-edge technology that enables the creation of three-dimensional objects by layering materials based on digital models. This innovation has transformed industries by offering enhanced design flexibility, reduced material waste, and cost-effective production, with applications spanning from prototyping and custom manufacturing to aerospace, healthcare, and the automotive sector (Gibson et al, 2015). Beyond revolutionizing traditional design and manufacturing processes, 3D printing has profoundly influenced various fields, including economics, geopolitics, sociology, environmental sustainability, demography, and security (Matias & Rao, 2015). A group of digital manufacturing technologies combined to create components layer by layer while using all available materials is known as 3D printing (West &Kuk, 2016; Sandström, 2016).

The true potential of 3D printing lies in its ability to drastically reduce the time required for large-scale production line adjustments while enabling continuous innovation during the manufacturing process. Simultaneously, this technology allows for mass production that is far more customizable to individual needs (Rayna & Striukova, 2016). The advancement and growth of manufacturing, retail, healthcare, and other industries are among the economic advantages of this technology (Jia et al, 2017). According to a recent survey by Allied Industry Research (AMR), the global 3D printing industry was estimated to be worth US $8.6 billion in 2020 and is expected to expand to US $15.6 billion by 2030, at a compound annual growth rate (CAGR) of 20.6%.

Although 3D printing has many benefits for businesses, its application is still rather limited. According to relevant studies, for instance, fewer than 2% of the manufacturing market still uses 3D printing (Wohlers et al, 2016). Furthermore, a lot of manufacturing companies are still having trouble optimizing their production lines and goods using this promising technology. In general, it appears that companies are facing significant challenges as a result of the widespread use of 3D printing.

Selecting a 3D printer for a specific industrial application is a complex decision-making problem that requires evaluating multiple conflicting criteria, such as cost, print quality, material compatibility, speed, reliability, ease of maintenance, and environmental impact (Gibson et al, 2015; Berman, 2012; Guo & Leu, 2013). Since no single 3D printer excels in all these aspects simultaneously, trade-offs must be made based on user priorities. Multi-criteria decision-making (MCDM) methods provide structured frameworks to systematically assess these criteria, assign appropriate weights, and rank alternatives objectively, ensuring a balanced and rational selection process (Zavadskas et al, 2014). Without such an approach, decisions risk being subjective, inconsistent, or inefficient, potentially leading to suboptimal selections that may fail to meet operational requirements (Mardani et al, 2015). By using MCDM methods, decision-makers can quantify preferences, minimize biases, and align their selection with both technical and economic constraints, ultimately enhancing transparency and improving the likelihood of meeting long-term operational goals (Ford & Despeisse, 2016; Huang et al, 2013).

MCDM methods have emerged as indispensable tools in addressing complex decision problems that involve multiple conflicting criteria, particularly in engineering, business, sustainability, and industrial domains. These methods support decision-makers by offering systematic frameworks for evaluating alternatives based on diverse quantitative and qualitative factors. As highlighted by Kumar and Pamucar (2025), MCDM methods have evolved significantly over the past two decades, enabling better structuring, analysis, and resolution of real-world decision problems. MCDM methods have been widely applied across diverse sectors, demonstrating their adaptability to complex decision-making contexts. They have been used for personnel selection in the tourism industry (Genç et al, 2024), selection of automotive equipment (Komatina, 2025), evaluation of smog mitigation strategies in environmental and public health contexts (Kousar et al, 2025), and procurement decisions in defense, such as assault rifle selection (Radovanovic et al, 2024). Further applications include combat system selection (Tesic and Marinkovic, 2023), sustainability evaluations (Sahoo et al, 2025), financial performance assessments (Yalçın et al, 2025), and sensitivity analysis under uncertainty modeling (Więckowski & Sałabun, 2025). These developments highlight the importance of MCDM as a robust tool for intricate technical and strategic decisions, enabling transparent, data-driven choices in applications like high-performance 3D printer selection.

Despite the growing use of 3D printing in a variety of industries, current research on 3D printer selection is sometimes lacking in application specificity and depends primarily on subjective decision-making methods. Most previous studies have focused on general-purpose use cases or prototyping requirements, with little attention paid to high-performance, end-use applications such as the production of racing car spoiler components that require a unique balance of precision, speed, material compatibility, and temperature stability. Furthermore, many of these studies use standalone MCDM approaches without incorporating objective weighting mechanisms, which might contribute to bias or inconsistency in criteria prioritisation. The market for 3D printers and related services, while still relatively small, is growing rapidly, making it increasingly important to select the most suitable option based on key factors such as cost efficiency, customization capabilities, and performance effectiveness. This study fills these gaps by proposing an integrated Entropy-Compromise Ranking of Alternatives from Distance to Ideal Solution (CRADIS) model for identifying the best 3D printer for manufacturing racing car spoilers. In the proposed model, the Entropy method has been used to evaluate the objective weights of criteria based on data variability. This approach reduces subjectivity and improves the reliability of the decision-making process. The CRADIS method is then employed to rank the 3D printers by calculating their distances from the ideal and anti-ideal solutions, providing a systematic and robust ranking framework. These two methods ensure a comprehensive evaluation, enabling decision-makers to balance technical requirements and economic constraints effectively. In addition, this study also conducts a comparative analysis with other prevalent MCDM methods to assess the stability and consistency of the rankings generated. This multi-method validation increases the trustworthiness of the results. To demonstrate the practical application of this approach, a case study is considered involving 16 alternative 3D printers evaluated against eight key selection criteria. This systematic methodology enhances decision-making transparency and ensures the selection of a 3D printer that optimally meets the specific needs of industrial applications, such as the production of high-performance racing car spoilers. This study makes a significant contribution to the literature by aligning the selection framework with the specific performance demands of racing car components and applying a rigorous, objective, and comparative MCDM approach. It also serves as a practical decision-support tool for engineers and practitioners in the automotive and motorsport industries.

Literature review

Paul et al. (2015) evaluated three MCDM methods for selecting 3D printers. The analytical Network Process (ANP) was used to determine criteria weights. The ranking methods included Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Deng’s Similarity-Based Approach, and Preference Ranking Organization Method for Enrichment Evaluations and Geometrical Analysis for Interactive Aid

(PROMETHEE-GAIA). Vinodh and Shinde (2018) optimized process parameters for Fused Deposition Modeling (FDM) in 3D printing. The multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method was used for optimization. Yeh and Chen (2018) developed a hybrid approach integrating Analytic Hierarchy Process (AHP) with the Technology-Organizational-Environment (TOE) framework to evaluate 3D printing adoption in Taiwanese manufacturing enterprises. The findings provided decision-makers with key insights for strategic adoption. Wang et al. (2018) introduced a system framework enabling customers to explore 3D printer alternatives based on their preferences. A case study demonstrated the benefits of allowing users to define acceptable levels, showing that a modified TOPSIS method achieved greater accuracy than the traditional approach. Khamhong et al. (2019) evaluated 3D printer selection criteria using Fuzzy AHP. The study analyzed decision-making perspectives of technical experts and users to determine optimal criteria weights. Prabhu et al. (2020) developed an MCDM model for selecting 3D printers based on criteria such as print volume, speed, and cost. The Preference Selection Index (PSI) method was employed, with Wanhao Duplicator 4 emerging as the best choice for racing car applications. Raigar et al. (2020) developed a decision support system for selecting an additive manufacturing process. A hybrid MCDM model was applied, combining Best Worst Method (BWM) for criteria weighting and Proximity Indexed Value (PIV) method for ranking. A spur gear model was fabricated using four AM processes, and sensitivity analysis validated the results. Lai and Chang (2021) proposed a two-stage evaluation approach for technology adoption. The first stage identified criteria using expert interviews and fuzzy Delphi, while the second stage used ANP for decision-making. Raja and Rajan (2022) examined the selection of an FDM machine for an Indian nongovernment organization based on nine criteria. The study recommended a suitable FDM machine among nine alternatives based on expert suggestions, aiding in machine selection for prototype production. Chatterjee and Chakraborty (2023) applied Evaluation Based on Distance from Average Solution (EDAS) method for selecting 3D printing nozzle materials. They considered eight alternative materials and nine criteria, incorporating sensitivity analysis to measure the robustness of the methodology. Nagarajan et al. (2023) proposed a group decision-making method for selecting 3D printing technologies. The study used neutrosophic ensembles to handle uncertainty and ambiguity, enabling efficient group decision-making. Wang et al. (2023) proposed a nonlinear Fuzzy Graph Model (FGM) combined with a dependency-considered fuzzy VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method.

Table 1 - Researcher contributions in 3D printer selection

Study	Methodology Used	Key Findings & Contributions
Paul et al. (2015)	ANP, TOPSIS, Deng's Similarity, PROMETHEE, GAIA	Compared MCDM techniques for 3D printer selection
Vinodh & Shinde (2018)	MOORA	Optimized FDM process parameters
Yeh & Chen (2018)	AHP, TOE framework	Examined 3D printing adoption in manufacturing
Wang et al. (2018)	Modified TOPSIS	Enhanced customer decision-making for 3D printer selection
Khamhong et al. (2020)	Fuzzy AHP	Assessed criteria for 3D printer selection
Prabhu et al. (2020)	PSI method	Identified optimal 3D printer for specific applications
Raigar et al. (2020)	BWM, PIV, sensitivity analysis	Developed a decision support system for AM selection
Lai & Chang (2021)	Fuzzy Delphi, ANP	Proposed a two-stage evaluation model for technology adoption
Raja & Rajan (2022)	Expert opinion-based ranking	Selected FDM machine for NGO use
Chatterjee & Chakraborty (2023)	EDAS, sensitivity analysis	Selected 3D printing nozzle materials
Nagarajan et al. (2023)	Neutrosophic ensembles	Addressed uncertainty in AM decision-making
Wang et al. (2023)	FGM, fuzzy VIKOR	Developed a dependency-considered 3D printer evaluation model
Sellamuthu et al. (2024)	MCDM, MEREC, MABAC	3D printer nozzle material selection
Yildirim & Ayyildiz,(2025)	MCDM, BWM, FF-WASPAS	Selecting the most suitable 3D printing technology for custom manufacturing

The proposed method incorporated interdependencies between criteria for comprehensive 3D printer evaluation. Sellamuthu et al. (2024) introduced an MCDM approach for selecting optimal materials for 3D printer nozzles by applying an integrated method based on the removal effects of criteria (MEREC)-multi-attributive border approximation area comparison (MABAC) methods to determine both the criteria weights and material performance. Yildirim and Ayyildiz (2025) proposed the first hybrid Fermatean fuzzy MCDM framework to evaluate six leading 3D printing technologies based on nine criteria, combining BWM for criteria weighting with fuzzy weighted aggregated sum product assessment (WASPAS) for alternative ranking. Table 1 shows the researcher's contributions in 3D printer selection by MCDM methods.

Methods

In this paper, the Entropy method is employed to determine the weights of the criteria, while the CRADIS method is used to rank the alternatives based on the established criteria. The entropy method is a widely accepted technique for calculating objective weights, as it measures the uncertainty or dispersion in the data, ensuring that the weights are derived based on the intrinsic information of the criteria (Shannon, 1948). This approach is particularly useful in MCDM problems, as it minimizes subjective bias in weight assignment.

CRADIS, on the other hand, is a well-established MCDM method that ranks alternatives by evaluating their distances from both the ideal and anti-ideal solutions. This method is highly regarded among decision-makers due to its ability to provide a balanced and comprehensive assessment of alternatives (Puška et al, 2022). To apply the CRADIS method, it is essential to first construct a decision-making matrix that evaluates the performance of each alternative against the selected criteria. This matrix serves as the foundation for subsequent calculations, enabling a systematic comparison of alternatives.

The integration of the Entropy method for weight determination and the CRADIS method for ranking offers a robust framework for addressing complex decision-making problems. By combining these methods, the study ensures that the criteria weights are objectively derived, while the ranking of alternatives is conducted in a structured and transparent manner. This approach not only enhances the reliability of the decision-making process but also provides a clear and defensible rationale for the final rankings.

The Entropy method

Shannon (1948) introduced the concept of entropy in the context of communication theory as a measure of uncertainty or information loss in data transmission, particularly to address issues related to missing and ambiguous data. This mathematical formulation of entropy quantifies the unpredictability or randomness in a system, making it a powerful tool for analyzing information systems. Zeleny (2012) highlighted the effectiveness of entropy as a tool for determining objective weights in decision-making processes. By measuring the dispersion or variability of data, entropy helps to assign weights to criteria in a way that minimizes subjective bias, ensuring a more balanced and rational evaluation of alternatives. The adaptability of the entropy concept to decision-making problems lies in its ability to quantify the relative importance of criteria based on the inherent information contained within the data. This makes it particularly useful in scenarios where decision-makers must evaluate multiple conflicting criteria and alternatives. The entropy method involves the following key steps:

Step 1: The method begins by establishing a decision matrix consisting of m alternatives and n criteria. Each element in the matrix represents the performance value (x_{ij}) of an alternative (i) with respect to a specific criterion (j).

Step 2: Normalize the decision matrix to ensure that all criteria values are on a comparable scale. For beneficial criteria (where higher values are better), normalization is done by dividing each value by the maximum value in that criterion (Equation 1). This scales all values between 0 and 1, preserving the relative performance and ensuring comparability across criteria. For non-beneficial criteria (where lower values are preferred), normalization is performed by dividing the minimum value by each value (Equation 2). This inversely scales the values so that better (lower) original values correspond to higher normalized scores. This step is particularly important when criteria are measured in different units.

$$n_{ij}=\frac{x_{ij}}{x_{jmax}}, \text{ for Beneficial Criteria} \quad (1)$$

$$n_{ij}=\frac{x_{jmin}}{x_{ij}}, \text{ for Non Beneficial Criteria} \quad (2)$$

Step 3: Calculate the entropy value for each criterion j as follows:

$$E_j=-\frac{\sum_{i=1}^{m}(P_{ij} * \ln P_{ij})}{\ln m} \quad (3)$$

The entropy value for each criterion j is calculated to measure the degree of disorder or uncertainty in the decision data. For the sake of ease of calculation, $(P_{ij} * \ln P_j)$ is defined as zero whenever $P_{ij} = 0$ in the actual evaluation using entropy method. The entropy value E_j ranges between 0 and 1. A higher entropy value indicates greater uncertainty or less useful information in criterion j, while a lower entropy value suggests that the criterion provides more discriminative information for decision-making.

Step 4: Calculate the weight (W_j) of each criterion as follows:

$$W_j = \frac{1-E_j}{\sum_{j=1}^{n}(1-E_j)} \quad (4)$$

where ($1-E_j$) indicates degree of diversification for criterion j. A higher ($1-E_j$) value indicates that the criterion carries more useful information for distinguishing among alternatives.

The CRADIS method

CRADIS, developed by Puška et al. (2022), is a robust MCDM method that merges the core advantages of Additive Ratio ASsessment (ARAS), Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS), and TOPSIS methods. Its design aims to reduce the possibility of rank reversal and presents a balanced mechanism for selecting optimal alternatives by accounting for deviations from both ideal and anti-ideal solutions. This dual-reference perspective offers a more comprehensive understanding of the relative performance of alternatives. CRADIS also enables flexible integration of various distance and weighting strategies, allowing it to be tailored to diverse decision-making environments (Wang et al, 2022). Additionally, it provides a simplified and interpretable structure compared to more complex models, enhancing its applicability across industrial applications (Zhang & Esangbedo, 2025). The CRADIS Method has been proven useful in complex domains like occupational risk assessment and sustainable infrastructure investment (Chakraborty et al, 2023). The CRADIS method has the following eight simple steps:

Step 1: Development of the decision matrix. The values of the alternatives according to the observed criteria make up the initial decision matrix.

Step 2: Normalization of the decision matrix. Normalization is performed based on equations (1) and (2).

Step 3: Weighting the normalized decision matrix. Aggravation of decision-making matrices. The aggravated decision matrix is obtained by multiplying the value of the normalized decision matrix by corresponding weights, based on the following expression:

$$V_{ij} = n_{ij} * w_j \quad (5)$$

Step 4: Determination of ideal (T_i) and anti-ideal (T_{ai}) solutions for each criterion. T_i corresponds to the highest value in the weighted decision matrix, whereas T_{ai} corresponds to the lowest value.

$t_i = \max V_{ij}$ (6)

$t_{ai} = \min V_{ij}$ (7)

Step 5: Calculation of deviations from T_i and T_{ai}. In this step, the weighted normalized values are subtracted from the maximum or minimum value.

$d^+ = t_i - V_{ij}$ (8)

$d^- = V_{ij} - t_{ai}$ (9)

Step 6: Calculation of the deviation score of individual alternatives from T_i and T_{ai}. Here, deviations are summed up and optimal alternatives are determined by the following expression:

$S_i^+ = \sum_{j=1}^{n} d^+$ (10)

$S_i^- = \sum_{j=1}^{n} d^-$ (11)

Step 7: Calculation of the utility function for each alternative in relation to the deviations from the optimal alternatives. In this step, each alternative is compared with respect to the optimal alternatives:

$K_i^+ = \frac{S_O^+}{S_i^+}$ (12)

$K_i^- = \frac{S_i^-}{S_O^-}$ (13)

where S_O^+ is an optimal alternative from T_i, while S_O^- is an optimal alternative from T_{ai}.

Step 8: Ranking alternatives, the final order is obtained by looking for the average deviation of the alternatives from the degree of utility:

$Q_i = \frac{K_i^+ + K_i^-}{2}$ (14)

The best alternative is the one that has the highest value of Q_i.

Case study

A spoiler, in the context of racing cars, is a device designed to disrupt and manage airflow over the vehicle. Figure 1 shows a high-performance rear spoiler designed to enhance aerodynamic efficiency by generating downforce at high speeds. It features a dual-bracket support structure for stability and adjustable mounting, commonly used in motorsport and performance vehicles for improved control. The primary purpose is to improve aerodynamic performance and increase stability at high speeds (Eftekhari et al, 2023). The main function of a spoiler is to generate downforce, which is a downward aerodynamic force that helps increase the grip and traction of the tires on the road (Zhang et al, 2006). This effect is particularly crucial when racing cars are traveling at high speeds or when cornering at high g-forces. Downforce improves overall handling and stability, allowing drivers to maintain control and achieve faster lap times (Katz, 2006). While spoilers primarily create downforce, they can also help reduce drag under certain conditions (Nath et al, 2021).Interestingly, the positioning of spoilers or rear wings can significantly impact their effectiveness. Research has shown that an optimal automobile downforce-to-drag ratio is achieved when the rear wing is placed at 39% of the height between the upper surface of the automobile trunk and the automobile roof (Buljac et al, 2016). Additionally, the use of Gurney Flaps on front wings has been found to increase downforce by about 24% with only a limited increase in drag force (Basso et al, 2021).

Figure 1 - Racing car spoiler

Thus, it is essential to produce suitable spoilers for racing cars using an appropriate 3D printing machine. Accordingly, the selection of 3D printers is based on the criteria listed in Table 2.

Criteria like energy consumption and software compatibility were excluded to focus on key factors like PV, MPS, and temperature that directly impact spoiler manufacturing. Energy use has minimal effect on quality, and most printers support standard software with little impact on results. Among the considered criteria, four criteria are beneficial (higher is better), and the remaining four are non-beneficial (lower is better) in nature. PV (beneficial) is an essential factor to consider when selecting a 3D printer, and it's crucial for several reasons like size of object, efficiency, design flexibility, reduced assembly, cost effectiveness and scale of production. MPS is critical and beneficial in 3D printing selection due to its impact on time efficiency, productivity, cost savings, competitive advantage, workflow optimization, and the balance between speed and print quality.

Table 2 - Criteria for 3D printer selection

Sl. No.	Criteria	Reference
1	Print volume (cu. mm) (PV)	Prabhu et al. (2020)
2	Max Print Speed (mm/sec) (MPS)	Prabhu et al. (2020), Ansari & Kamil (2021)
3	Layer Thickness (µm) (LT)	AlRumaih & Gad (2024)
4	No. of Extruders (NE)	Prabhu et al. (2020)
5	Machine Cost ($) (C)	Prabhu et al. (2020)
6	Manufacturer Filament Price ($/kg) (MFP)	Prabhu et al. (2020), Shaharuzaman et al. (2024)
7	Max Extruder Temperature (°C) (MET)	Ansari & Kamil (2021)
8	Max Bed Temperature (°C) (MBT)	Choi et al. (2016), Shaharuzaman et al. (2024)

Evaluating print speed alongside other factors such as PV, print resolution, material compatibility, and software capabilities can help to select a 3D printer that aligns with the needs and priorities. LT (non-beneficial) plays a crucial role in determining the resolution, surface finish, accuracy, strength, print speed, material compatibility, and support structure requirements of 3D-printed objects. Evaluating the ideal LT for any specific applications and balancing it with other factors such as MPS and material properties can help to achieve optimal results. NE in a 3D printer is decisive for multi-material printing, color variation, support material deposition, efficiency, productivity, tool changing capabilities, material mixing, flexibility, versatility, and achieving complex details in prints. Assessing the specific printing needs, material requirements, and desired functionalities can help to determine whether a printer with multiple extruders is suitable for the applications. C is a non-beneficial criterion in 3D printing selection due to its implications on initial investment, budget allocation, rate of interest (RoI), total cost of ownership, technology features, scalability, market competition, and overall cost-effectiveness. Balancing machine cost with performance, reliability, support, and long-term value is essential to make informed decisions and achieve desired outcomes in additive manufacturing applications. MFP is significant and non-beneficial in 3D printing selection as it influences cost management, budget constraints, material variety, print quality, reliability, long-term savings, and access to technical support. Evaluating MFP alongside other factors such as filament properties, compatibility, and manufacturer reputation can help users make informed decisions when selecting filaments for 3D printing applications. MET is vital in 3D printing selection because it directly influences material compatibility, print quality, layer adhesion, filament flow, printing speed, material properties, and multi-material printing capabilities. Ensuring that a 3D printer extruder can reach and maintain the necessary temperatures for the chosen filaments is key to successful and reliable 3D printing operations. MBT in 3D printing selection for spoiler production is significant because it directly impacts adhesion, warping prevention, print quality, material compatibility, ease of print removal, and the versatility of materials that can be used in spoilers manufacturing. Ensuring that the heated bed of the 3D printer is set to the appropriate temperature for the chosen material is essential for achieving successful and high-quality prints. Table 3 presents the decision matrix developed for selecting 3D printer suitable for manufacturing spoilers for racing cars. The data of 16 printers with respect to the criteria is collected from literature and various websites (Prabhu et al, 2020; https://support.makerbot.com/s/article/1667337895715, https://www.3dwasp.com/en/delta-printer-delta-wasp-2040, https://www.treatstock.com/machines/item/342-up-plus-2)

Results and discussion

Application of Entropy - CRADIS method

Stage I: The Entropy Method (for criteria weighting)

At this stage, The Entropy method is employed to calculate the weights of the criteria used for selecting 3D printer for manufacturing racing car spoilers. First, the decision matrix is normalized using equations (1) and (2) for beneficial and non-beneficial criteria, respectively. The resulting normalized matrix is presented in Table 4. Subsequently, entropy values for each criterion are calculated using equation (3). Finally, the criteria weights shown in Table 5 are derived using equation (4). Based on Table 5, C2 and C3 emerge as the most significant criteria, while C8 is identified as the least significant.

Stage II: The CRADIS Method (for ranking alternatives)

In this stage, the CRADIS method is applied to determine the ranking of the alternatives. Equations (5), (6), and (7) yield the weighted normalized matrix with ideal and anti-ideal solutions. The lowest values across all criteria are represented by the anti-ideal solution (Tai), which also includes the highest values. The anti-ideal solution (Tai) is in opposition to the ideal solution (Ti), as shown in Table 6.

Table 3 - Decision matrix for 3D printer selection for racing car spoiler

3D printer	PV	MPS	LT	NE	C	MFP	MET	MBT
Ultimaker 2 (A1)	230 x 225 x 205	300	20	1	2750	49.95	260	120
Zortrax (A2)	200 x 200 x 185	100	90	1	1990	59.00	380	110
Printrbot simple (A3)	150 x 150 x 150	80	100	1	999	28.00	220	80
Lulzbot Taz 6 (A4)	280 x 280 x 250	200	50	2	2500	65.00	240	110
Wanhao duplicator 4 (A5)	225 x 145 x 150	50	100	1	829	24.00	260	85
XYZ Da Vinci 1.0 (A6)	200 x 200 x 200	150	100	1	379	46.65	215	90
Airwolf 3D AW3D HD2X (A7)	280 x 200 x 300	150	60	1	3994	48.00	315	120
Afinia H+1 (A8)	255 x 205 x 225	200	150	1	1599	70.00	250	100
Ditto Pro (A9)	370 x 390 x 436	120	50	1	1899	45.00	280	80
Flashforge Creator X (A10)	225 x 145 x 150	100	100	2	2999	25.99	320	110
Felix 3.0 (A11)	255 × 205 × 235	150	50	1	1799	41.37	195	95
Makerbot Replicator Original (A12)	225 x 145 x 150	175	200	1	2000	33.00	230	100
Mbot Grid 2+ (A13)	235 x 210 x 180	120	100	2	1099	32.00	260	110
Delta non-turbo WASP 2040 (A14)	200 × 200 × 400	300	50	1	2999	24.00	350	100
Artifex duo 2 (A15)	156 × 310 × 223	150	50	2	1901	26.30	235	90
UP Plus 2 (A16)	140 x 140 x 135	30	150	1	850	55.00	260	100

The first and third values (0.169 and 1.000) in Table 4 have been calculated using equations (1) and (2) for the beneficial and non-beneficial criteria, respectively, as follows:

$$n_{11} = \frac{230 * 225 * 205}{370 * 390 * 436} = 0.169$$

$$n_{13} = \frac{20}{20} = 1$$

Table 4 - Normalized decision matrix for 3D printer selection of spoiler

3D printer	PV	MPS	LT	NE	C	MFP	MET	MBT
A1	0.169	1.000	1.000	0.500	0.138	0.480	0.684	0.667
A2	0.118	0.333	0.222	0.500	0.190	0.407	1.000	0.727
A3	0.054	0.267	0.200	0.500	0.379	0.857	0.579	1.000
A4	0.312	0.667	0.400	1.000	0.152	0.369	0.632	0.727
A5	0.078	0.167	0.200	0.500	0.457	1.000	0.684	0.941
A6	0.127	0.500	0.200	0.500	1.000	0.514	0.566	0.889
A7	0.267	0.500	0.333	0.500	0.095	0.500	0.829	0.667
A8	0.187	0.667	0.133	0.500	0.237	0.343	0.658	0.800
A9	1.000	0.400	0.400	0.500	0.200	0.533	0.737	1.000
A10	0.078	0.333	0.200	1.000	0.126	0.923	0.842	0.727
A11	0.195	0.500	0.400	0.500	0.211	0.580	0.513	0.842
A12	0.078	0.583	0.100	0.500	0.190	0.727	0.605	0.800
A13	0.141	0.400	0.200	1.000	0.345	0.750	0.684	0.727
A14	0.254	1.000	0.400	0.500	0.126	1.000	0.921	0.727
A15	0.171	0.500	0.400	1.000	0.199	0.913	0.618	0.889
A16	0.042	0.100	0.133	0.500	0.446	0.436	0.684	0.800

The weight of criterion PV (0.130), as presented in Table 5, is calculated using equations (3) and (4) as follows:

$$E_1 = (-3.976) * (-0.361) = 1.434$$

$$W_1 = \frac{1 - 1.434}{-3.331} = 0.130$$

Table 5 - Weights of 3D printer selection criteria for spoiler

Criteria	PV	MPS	LT	NE	C	MFP	MET	MBT
Weight	0.130	0.197	0.231	0.150	0.135	0.036	0.110	0.011

The weighted normalized value of 0.022 for the alternative A1 under the first criterion PV, is calculated using equation (5). Subsequently, maximum (T_i) and minimum (T_{ai}) values are determined using equations (6) and (7), respectively, as shown in Table 6.

$V_{11} = 0.169 * 0.130 = 0.022$

Ti = 0.130, Tai = 0.005

Equations (8) and (9) are then used to determine the deviation from T_i and T_{ai}, as shown in Tables 7 and 8.

Table 6 - Weighted normalized decision matrix with T_i and T_{ai} values

3D printer	PV	MPS	LT	NE	C	MFP	MET	MBT
T_i	0.130	0.200	0.230	0.150	0.140	0.040	0.110	0.010
A1	0.022	0.200	0.230	0.075	0.019	0.019	0.075	0.007
A2	0.015	0.067	0.051	0.075	0.027	0.016	0.110	0.007
A3	0.007	0.053	0.046	0.075	0.053	0.034	0.064	0.010
A4	0.040	0.133	0.092	0.150	0.021	0.015	0.069	0.007
A5	0.010	0.033	0.046	0.075	0.064	0.040	0.075	0.009
A6	0.017	0.100	0.046	0.075	0.140	0.021	0.062	0.009
A7	0.035	0.100	0.077	0.075	0.013	0.020	0.091	0.007
A8	0.024	0.133	0.031	0.075	0.033	0.014	0.072	0.008
A9	0.130	0.080	0.092	0.075	0.028	0.021	0.081	0.010
A10	0.010	0.067	0.046	0.150	0.018	0.037	0.093	0.007
A11	0.025	0.100	0.092	0.075	0.029	0.023	0.056	0.008
A12	0.010	0.117	0.023	0.075	0.027	0.029	0.067	0.008
A13	0.018	0.080	0.046	0.150	0.048	0.030	0.075	0.007
A14	0.033	0.200	0.092	0.075	0.018	0.040	0.101	0.007
A15	0.022	0.100	0.092	0.150	0.028	0.037	0.068	0.009
A16	0.005	0.020	0.031	0.075	0.062	0.017	0.075	0.008
T_{ai}	0.005	0.020	0.023	0.075	0.013	0.014	0.056	0.007

The deviation value of 0.108 for alternative A1 with respect to Ti in Table 7 has been calculated as follows:

$$d_{11}^{+} = 0.130 - 0.022 = 0.108$$

In the next step, the grade of deviation for each alternative from T_i and T_{ai} values is determined using equations (10) and (11). Then, equations (12) and (13) are applied to calculate the utility function for each alternative based on the deviation from the optimal solutions. The final step in ranking the alternatives involves using equation (14) to compute the average deviation from the degree of utility. The results are shown in Table 9.

Table 7 - Deviation from T_i values

3D printer	PV	MPS	LT	NE	C	MFP	MET	MBT
A1	0.108	0.000	0.000	0.075	0.121	0.021	0.035	0.004
A2	0.115	0.133	0.179	0.075	0.113	0.024	0.000	0.003
A3	0.123	0.147	0.184	0.075	0.087	0.006	0.046	0.000
A4	0.090	0.067	0.138	0.000	0.119	0.025	0.041	0.003
A5	0.120	0.167	0.184	0.075	0.076	0.000	0.035	0.001
A6	0.113	0.100	0.184	0.075	0.000	0.019	0.048	0.001

3D printer	PV	MPS	LT	NE	C	MFP	MET	MBT
A7	0.095	0.100	0.153	0.075	0.127	0.020	0.019	0.004
A8	0.106	0.067	0.199	0.075	0.107	0.026	0.038	0.002
A9	0.000	0.120	0.138	0.075	0.112	0.019	0.029	0.000
A10	0.120	0.133	0.184	0.000	0.122	0.003	0.017	0.003
A11	0.105	0.100	0.138	0.075	0.111	0.017	0.054	0.002
A12	0.120	0.083	0.207	0.075	0.113	0.011	0.043	0.002
A13	0.112	0.120	0.184	0.000	0.092	0.010	0.035	0.003
A14	0.097	0.000	0.138	0.075	0.122	0.000	0.009	0.003
A15	0.108	0.100	0.138	0.000	0.112	0.003	0.042	0.001
A16	0.125	0.180	0.199	0.075	0.078	0.023	0.035	0.002

The first deviation value 0.017 from Tai in the Table 8 has been calculated using equation (9) as follows:
$d_{11}^{-} = 0.022 - 0.005 = 0.017$

Table 8 - Deviation from T_{ai} values

3D printer	PV	MPS	LT	NE	C	MFP	MET	MBT
A1	0.017	0.180	0.207	0.000	0.006	0.006	0.019	0.000
A2	0.010	0.047	0.028	0.000	0.013	0.003	0.054	0.001
A3	0.002	0.033	0.023	0.000	0.040	0.021	0.007	0.003
A4	0.035	0.113	0.069	0.075	0.008	0.001	0.013	0.001
A5	0.005	0.013	0.023	0.000	0.051	0.026	0.019	0.003
A6	0.011	0.080	0.023	0.000	0.127	0.007	0.006	0.002
A7	0.029	0.080	0.054	0.000	0.000	0.006	0.035	0.000
A8	0.019	0.113	0.008	0.000	0.020	0.000	0.016	0.001
A9	0.125	0.060	0.069	0.000	0.015	0.008	0.025	0.004
A10	0.005	0.047	0.023	0.075	0.004	0.023	0.036	0.001
A11	0.020	0.080	0.069	0.000	0.016	0.009	0.000	0.002
A12	0.005	0.097	0.000	0.000	0.013	0.015	0.010	0.001
A13	0.013	0.060	0.023	0.075	0.035	0.016	0.019	0.001
A14	0.028	0.180	0.069	0.000	0.004	0.026	0.045	0.001
A15	0.017	0.080	0.069	0.075	0.015	0.023	0.012	0.002
A16	0.000	0.000	0.008	0.000	0.049	0.004	0.019	0.001

Deviation scores of alternative A1 with respect to T_i and T_{ai} (0.363 and 0.434 respectively), as shown in Table 9, are calculated using equations (10) and (11) as follows:

$$S_1^{+} = 0.108 + 0.000 + 0.000 + 0.075 + 0.121 + 0.021 + 0.035 + 0.004 = 0.363$$

$S_1^- = 0.017 + 0.180 + 0.207 + 0.000 + 0.006 + 0.006 + 0.019 + 0.000$
$= 0.434$

The utility functions (K_i^+ and K_i^-) of alternative A1 from the optimal deviation in Table 9 are 1.000 and 1.000, which has been calculated using equations (12) and (13) as follows:

S_1^+ = Optimal Value for K_i^+ = Minimum value in $S_i^+ = 0.363$

S_1^- = Optimal Value for K_i^-= Maximum value in $S_i^- = 0.434$

$$K_1^+ = \frac{0.363}{0.363} = 1.000$$

$$K_1^- = \frac{0.434}{0.434} = 1.000$$

The average deviation (Q_i) value of 1.000 for alternative A1 has been calculated using equation (14) as follows:

$$Q_1 = \frac{1.000 + 1.000}{2} = 1.000$$

The first rank is assigned based on the highest average deviation value. Among all the alternatives, Alternative 1 has the highest average deviation value of 1.000; therefore, it is ranked first.

Table 9 - Results of CRADIS method

3D printer	S_i^+	S_i^-	K_i^+	K_i^-	Q_i	Rank
A1	0.363	0.434	1.000	1.000	1.000	1
A2	0.642	0.155	0.565	0.357	0.461	12
A3	0.668	0.129	0.543	0.297	0.420	15
A4	0.482	0.315	0.753	0.726	0.740	3
A5	0.657	0.139	0.552	0.322	0.437	14
A6	0.541	0.256	0.671	0.589	0.630	6
A7	0.593	0.204	0.612	0.470	0.541	9
A8	0.620	0.177	0.586	0.408	0.497	11
A9	0.493	0.304	0.736	0.701	0.719	4
A10	0.583	0.214	0.622	0.493	0.558	8
A11	0.600	0.196	0.604	0.453	0.529	10
A12	0.655	0.141	0.554	0.326	0.440	13
A13	0.555	0.242	0.654	0.557	0.605	7
A14	0.444	0.353	0.817	0.813	0.815	2
A15	0.505	0.292	0.719	0.673	0.696	5
A16	0.716	0.081	0.507	0.186	0.346	16

Performance comparison and sensitivity analysis

Computation of ranking stability based on different MCDM method comparisons

A comparative performance study between this integrated method and the other six widely used MCDM methods like EDAS, COmbinative Distance-based Assessment (CODAS), MABAC, TOPSIS, PROMETHEE, and MARCOS is presented in order to determine the ranking of the considered 3D printers for racing car spoilers and to elucidate reliability of CRADIS method. These methods are selected due to their several benefits, broad range of applications and ability to effectively rank alternatives in MCDM environment. One of the recently developed MCDM methods is EDAS. According to the selected beneficial or non-benefit criteria, the distances in both the positive and negative directions are calculated using the average solution individually in this method (Ghorabaee et al, 2015). CODAS is considered an effective approach for evaluating alternatives. It employs l1- and l2-norm indifference spaces for criteria to assess the desirability of alternatives. The evaluation score is determined based on these spaces using a combination of Euclidean and Taxicab distances. Alternatives are ranked according to the evaluation results (Ghorabaee et al, 2016). The MABAC method is superior to many other conventional MCDM methods in a number of ways. No matter how many alternatives and criteria there are, mathematical formulas always remain the same. The core principle of the MABAC method is to evaluate the distance of each alternative's criteria function from the border approximation area (Pamucar & Cirovic, 2015). Both qualitative and quantitative criteria can be used with this method. According to Chang et al. (2010), TOPSIS is a significant distance-based method that ranks the alternatives according to their proximity to the ideal solution and their distance from the anti-ideal solution. Through the determination of the two distance measurements, this tool is useful and practical for the evaluation and selection of several reciprocally conflicting alternatives. PROMETHEE is an MCDM method used to rank alternatives based on multiple criteria or attributes and has been widely applied in various fields like business, engineering, environmental management, and public policy. The MARCOS method has the potential for subjectivity in assigning criteria weights and scores, reliance on accurate and reliable data for scoring alternatives, and the assumption of linear aggregation of criteria. The best alternatives are identified by the decision makers with the aid of the compromise solution.

Table 10 - Ranking stability analysis based on comparisons of various MCDM methods

3D printer	Rank						
	CRADIS	MABAC	MARCOS	CODAS	EDAS	TOPSIS	PROMETHEE
A1	1	2	1	1	1	2	3
A2	12	10	15	8	10	10	11
A3	15	13	13	14	14	11	14
A4	3	4	5	4	3	4	2
A5	14	12	8	16	13	12	13
A6	6	9	7	15	8	7	10
A7	9	11	11	9	9	8	8
A8	11	14	14	2	12	13	9
A9	4	5	9	6	4	1	5
A10	8	7	3	3	11	14	12
A11	10	8	10	13	6	6	6
A12	13	15	12	5	15	16	15
A13	7	6	6	7	7	9	7
A14	2	1	2	11	2	3	1
A15	5	3	4	10	5	5	4
A16	16	16	16	12	16	15	16

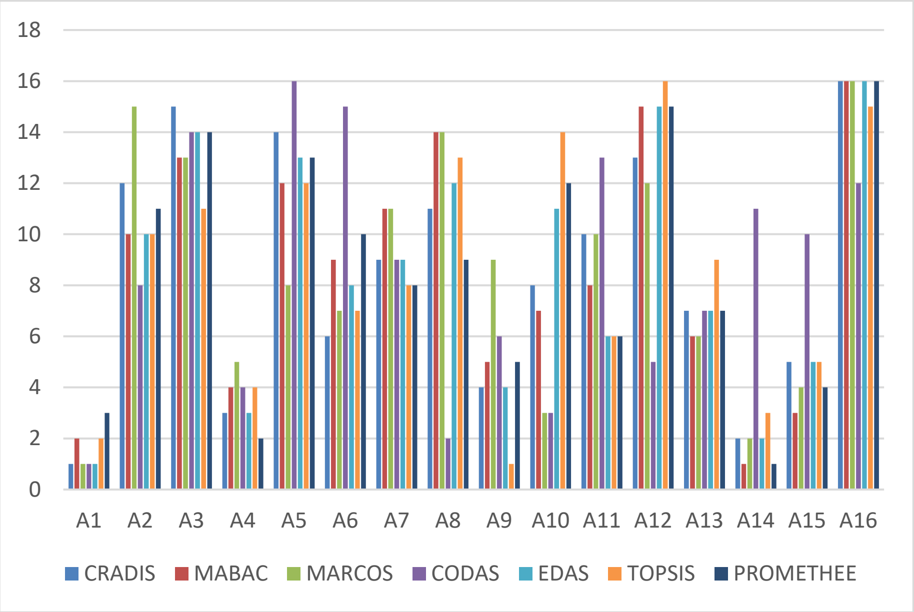

Figure 2 - Rankings of alternative 3D printers by different MCDM methods

Figure 2 illustrates the degree of similarity in the rankings obtained through the CRADIS method compared with the results from other MCDM methods. Table 10 presents the rankings derived from CRADIS and other MCDM methods. The results suggest that Ultimaker 2 (A1), Delta non-turbo WASP 2040 (A14), and Lulzbot Taz 6 (A4) are among the top alternatives for producing spoilers, whereas UP Plus 2 (A16) ranks lowest for this application.

Spearman rank correlation coefficient

Spearman's rank correlation coefficient is a non-parametric statistical measure used to assess the strength and direction of the relationship between two ranked variables. Unlike Pearson's correlation, which measures linear relationships, Spearman's correlation evaluates monotonic relationships, meaning that as one variable increases the other either consistently increases or decreases. It is calculated using the ranks of the data rather than the actual values, making it suitable for ordinal data or cases where the assumptions of normality and linearity are not met. The coefficient ranges from −1 (perfect negative correlation) to +1 (perfect positive correlation), with 0 indicating no correlation. It is widely used in fields such as psychology, economics, and social sciences to analyze relationships where data may not follow a normal distribution. Calculating the Spearman rank correlation coefficient allows for a comparison of the outcomes from various MCDM methods. An exceptional correlation between the rankings is indicated by a Spearman correlation coefficient value that is closer to 0.8 or higher. The Spearman correlation coefficient values between the various MCDM methods are displayed in Table 11. Table 11 demonstrates how well the ranking produced by CRADIS matches the ranking produced by the other MCDM methods. In the CODAS, all the values are less than 0.8, so this method exhibits an inappropriate correlation. The weaker correlation observed for the CODAS method can be attributed to its distinct evaluation mechanism. The CODAS method ranks alternatives based on their Euclidean and Taxicab distances from a negative-ideal solution, emphasizing how much worse an alternative is compared to the least desirable option. This contrasts with other methods that focus on closeness to an ideal solution or use aggregated scores. As a result, CODAS tends to penalize alternatives differently, especially when the performance values are marginal or closely clustered. Its sensitivity to distance-based dominance leads to rankings that can deviate significantly from those generated by methods using preference functions, normalization-based scoring, or utility-based evaluation.

Table 11 - Spearman's coefficient of the rankings obtained using different MCDM tools for 3D printing machine for spoiler

Method	CRADIS	MABAC	MARCOS	CODAS	EDAS	TOPSIS	PROMETHEE
CRADIS	1.0000	0.9235	0.8235	0.4000	0.9412	0.8412	0.9000
MABAC	0.9235	1.0000	0.8618	0.24412	0.9412	0.8441	0.8912
MARCOS	0.8235	0.8618	1.0000	0.2235	0.7353	0.5794	0.6735
CODAS	0.4000	0.24412	0.2235	1.0000	0.2618	0.0677	0.2882
EDAS	0.9412	0.9412	0.7353	0.2618	1.0000	0.9412	0.9647
TOPSIS	0.8412	0.8441	0.5794	0.0677	0.9412	1.0000	0.8941
PROMETHEE	0.9000	0.8912	0.6735	0.2882	0.9647	0.8941	1.0000

Conclusion

Selecting an appropriate 3D printer for producing spoilers for racing vehicle applications is one of the most difficult tasks because of the increasing complexity and cutting-edge features and capabilities that component designers and manufacturers are constantly adding to their creations. This study explores ways to help solve decision-making problems and offers information on a number of significant factors that should be taken into account for the best assessment and selection of 3D printing machines. In the current problem, the entropy-CRADIS method has been applied, and the ranking orders have been summarized. The strategy began with entropy and acquired weightage by maintaining cost reduction and surface finish as the primary objectives. When these weights are added to CRADIS, a ranking was produced, and the Delta non-turbo Ultimaker 2 (A1) came out on top. This method for choosing the best alternatives is very straightforward to understand and use. This strategy can also be applied to other decision-making scenarios with an infinite number of criteria and choices. With the aid of several MCDM methods, including EDAS, CODAS, MABAC, TOPSIS, PROMETHEE, and MARCOS, it is eventually determined that the best 3D printers for producing racing car spoilers are the Ultimaker 2 (A1), Delta non-turbo WASP 2040 (A14) and Lulzbot Taz 6 (A4). The Ultimaker 2 outperforms other 3D printers by offering a well-balanced combination of performance, material capability, and cost-effectiveness across key criteria. It provides a generous print volume suitable for most applications, along with a high maximum print speed that enhances productivity. Its ability to print with a fine layer thickness ensures high-resolution outputs, while a single extruder simplifies maintenance without compromising functionality. The printer is also competitively priced and uses moderately priced manufacturer filament, contributing to lower operating costs. Additionally, its maximum extruder temperature and bed temperature are sufficient for printing a wide range of materials, making it both versatile and efficient. This well-rounded performance across both technical and economic parameters positions the Ultimaker 2 as a leading choice in desktop 3D printing. The findings indicate that UP Plus 2 (A16) cannot be used for the above-mentioned purposes. The final results of Spearman's ranking coefficient demonstrated a strong association between each of the several MCDM methods. Future study can include testing the methodology with dynamic or context-sensitive criteria weights that reflect changing priorities, such as balancing cost and quality at different production stages or varying based on material type, manufacturing scale, or environmental constraints. Applying this MCDM approach to other automotive components like air intakes, diffusers, or interior trim parts can validate its versatility and adaptability to different performance requirements, such as airflow optimization or surface finish. However, this study is limited by its reliance on manufacturer-provided data and the use of static criteria weights, which may not fully capture real-world variability and evolving priorities. Addressing these limitations in future work will enhance the robustness and applicability of the approach. Incorporating real-world printing trials with top-ranked printers will further refine the model and ensure alignment with actual manufacturing conditions, supporting broader adoption in automotive design and prototyping.

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Izbor 3D štampača za spojlere trkačkih automobila korišćenjem modela ,,Entropy – CRADIS"

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Sažetak:

Uvod/cilj: Cilj ovog istraživanja je da identifikuje najprikladniji 3D štampač za proizvodnju spojlera za trkačke automobile.

Metode: Šesnaest različitih 3D štampača je evaluirano na osnovu osam kriterijuma izbora, uključujući zapreminu štampe, maksimalnu brzinu štampe, debljinu sloja, broj ekstrudera, cenu mašine, cenu filamenta kod proizvođača, maksimalnu temperaturu ekstrudera i maksimalnu temperaturu radne površine. Težine kriterijuma su određene korišćenjem metode Entropy, dok je metoda kompromisnog rangiranja alternativa prema udaljenosti od idealnog rešenja (eng. CRADIS) primenjena za rangiranje mašina i pronalaženje najbolje opcije za proizvodnju spojlera. Za validaciju rezultata sprovedena je analiza osetljivosti korišćenjem različitih metoda.

Rezultati: Ultimaker 2 je identifikovan kao najprikladniji 3D štampač, sledi Delta Non-Turbo WASP 2040, dok UP Plus 2 zauzima najnižu poziciju.

Zaključak: Korišćenjem metoda Entropy i CRADIS, Ultimaker 2 je identifikovan kao 3D štampač sa najboljim performansama. Sledi Delta Non-Turbo WASP 2040, dok je UP Plus 2 rangiran kao najmanje pogodan. Različite višekriterijumske metode odlučivanja (MCDM) su primenjene za poređenje performansi i analizu osetljivosti, dok je Spirmanov koeficijent korelacije rangova korišćen za procenu korelacije između različitih metoda odlučivanja.

Ključne reči: aditivna proizvodnja, 3D štampanje, višekriterijumsko odlučivanje, Entropy, CRADIS, analiza osetljivosti.

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