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Original Article

Comparative Evaluation of Rapid Prototyping Processes for Product Development Using Optimization Techniques

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Abstract - *Creating innovative products within stringent timeframes presents a significant hurdle for small-scale manufacturers, highlighting the necessity for innovative solutions. To develop products effectively, it is essential to have a deep understanding of the complex interplay between product features, manufacturing processes, and market requirements. In this context, a technique known as Rapid Prototyping (RP) has emerged as a promising solution, but its successful implementation relies on specialized expertise and the ability to navigate intricate variables. For example, the design and optimization of water sprinklers offer opportunities for innovation in both commercial and agricultural contexts, with key factors such as water pressure and coverage playing a crucial role. Regular testing of prototypes ensures the efficacy of these systems, making RP the preferred method for prototyping. However, the implementation of RP is often hindered by a lack of skilled expertise and the complexity of process parameters. This research conducts a comparative evaluation of RP methods, using a decision-making approach that considers multiple criteria to assess product attributes such as surface finish, production duration, accuracy, strength, and cost. This MCDM approach enables ranking of available methods. The fundamental objective of the mentioned study is to calculate the most suitable RP method for manufacturing prototypes of sprinkler system components, enabling small scale manufacturers to develop innovative products efficiently and effectively.*

Keywords - *MCDM techniques, Product attributes, Prototype, Ranking of RP method.*

1. Introduction

In today's business landscape, companies believe in product development and modification to stay ahead of the competition. These modifications can be minor, such as tweaking the design or enhancing the aesthetics, or major, involving a complete overhaul of the product. To successfully implement these changes, organizations must conduct a thorough assessment of their internal capabilities and vendor partnerships to ensure they can accommodate the modifications. Effective planning requires careful consideration of several key factors, including the manufacturing requirements for specialized equipment, the need for additional inspection tools, and the adaptability of machinery to accommodate product changes. Creating physical prototypes allows companies to visualize and address potential issues, ensuring a smooth transition. When choosing the best method from a range of options, designers must carefully evaluate each alternative's unique characteristics, applications, benefits, and drawbacks. A deep knowledge of the functional needs for individual components, as well as the specific design scheme, is essential. Selecting the wrong method can result in significant costs and premature component failure, making it a critical challenge for designers to identify the optimal approach for diverse engineering applications. To overcome these challenges, designers must:

1. Select materials and methods with specific functionalities.
2. Balance desired outcomes with minimal costs.
3. Adopt a systematic approach to process selection.

RPT does not need special tooling like injection molding; instead, it uses support structures. Availability of methods and capabilities, like material suitability—as different materials like polymers and metals can be used—is considered. Product design changes are possible at any stage of manufacturing. Any design change or product stage is observed at the time of manufacturing [1].

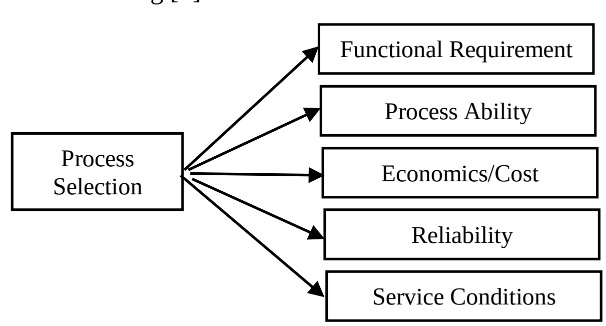

Fig. 1 Process selection parameters

1.1. Rapid Prototyping and Its Industrial Relevance

Rapid prototyping refers to a collection of methods that enable the fast creation of physical models or components directly from 3D Computer-Aided Design (CAD) files. These techniques allow designers and engineers to quickly produce scaled-down versions of parts or assemblies, helping in the visualization and evaluation of design concepts before full-scale production. The current era of Industrie 4.0 demands rapid development and rapid response to customers. RPTs are used mostly for rapid response with higher accuracy. Various technologies in RPT, like Selective Laser Sintering (SLS), Stereolithography (SLS), 3D printing (3DP), and Fused deposition method (FDM), are available in the market. Every method has its own characteristics and development time, with the desired attributes of the product. The widespread adoption of rapid prototyping (RP) technologies presents educational institutions and manufacturing organizations with a complex challenge: selecting the optimal system from numerous options. To make informed decisions, they must carefully evaluate each system's capabilities, features, and applications. RP technologies leverage additive manufacturing techniques, enabling the creation of intricate physical prototypes through layer-by-layer deposition. This transformative process revolutionizes traditional manufacturing methodologies, offering unparalleled design flexibility and efficiency [2, 3]. Due to a number of rapid prototyping technologies available in the market, appropriate technology selection is difficult.

The selection of proper processes is a multitasking and complex process. It's sensitive for users by RP experience to consider an appropriate process reason, as there are numerous RP systems all over the world, and the formal selection varies according to numerous concepts. Similar products with slight changes in them may be most liable to the change in molds / conventional manufacturing methods, which proves to be costly to the manufacturer. Small-scale industries may not sustain these variations at a rapid pace, and hence a new technique is desirable that is easy to identify, select, implement and cost-effective. The applications of RPT involve providing design, function, end use or manufacturing prototypes. These prototypes help in decreasing the development lead time in many of the applications. Process selection complexity creates doubts in its implementation. Product quality and its costing are the main focus of this product development work.

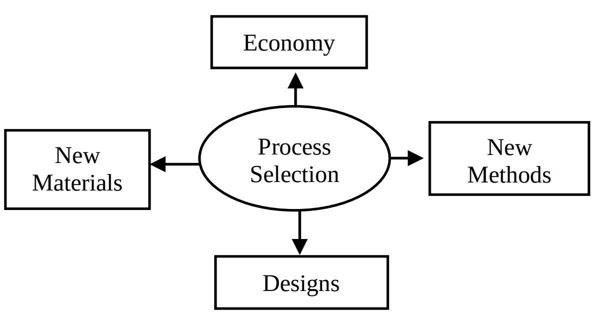

Fig. 2 Process selection complexity

1.2. Rapid Prototyping Methods and their Selection

Rao and Padmanabhan [2] pioneered a groundbreaking methodology for selecting optimal rapid prototyping (RP) methods tailored to specific part applications. By integrating graph theory and matrix analysis, their approach systematically evaluates RP process selection criteria and their accurate importance within the context of the intended application. Bahnini et al. [4] performed a comparative assessment of traditional (RP) manufacturing processes. Their study systematically examined various aspects of additive manufacturing, including its prospects, current status, and applications. Mançanares et al. [5] developed a decision-making model for optimizing the sequence and ranking of rapid prototyping (RP) methods. They leverage the “Analytical Hierarchy Process (AHP) to estimate and prioritize the most capable technologies & machines”, which means these methods provide appropriate weights to individual attributes. Many important Machine parameters are considered in the AHP-based selection process, ultimately yielding a ranked assessment of manufactured parts. Lan [6] introduced a collaborative framework enabling users and rapid prototyping (RP) manufacturers to interact remotely. This approach facilitates the sharing of manufacturing facilities and enhances their availability. Lan proposed an integrated manufacturing system combining RP and traditional manufacturing. The web-based Rapid Prototyping Technology (RPT) model supports remote services and manufacturing for rapid prototyping products.

1.3. Multi-Criteria Decision-Making Techniques

Wang et al. proposed an innovative hybrid MCDM approach, combining design of experiments (DOE) and grey relational analysis (GRA) to form a robust decision-making framework, referred to as the DOE-GRA model. This methodology addresses process selection challenges in multi-criteria scenarios. To validate its effectiveness, three case studies were analyzed: fast prototyping procedure selection, lenient manufacturing system evaluation, and automated inspection system choice. Comparative results reveal that the DOE-GRA method exhibits minimal sensitivity to weight fluctuations, offers straightforward and rapid calculations, and demonstrates robustness and practicality, making it well-suited for MCDM applications [7, 24, 25]. Karande and Chakraborty [9] investigated the app of the “MOORA” method in material selection, focusing on multi-objective optimization. Their research assessed the “reference point strategy & full multiplicative MOORA” method, providing insights into their problem-solving capabilities. Chatterjee and Chakraborty [10] explored the potential of the ORESTE method in addressing complex AMS selection challenges. Five diverse case studies demonstrated its effectiveness in evaluating industrial robots, flexible manufacturing systems, rapid prototyping processes, manufacturing cell machines, and non-traditional machining processes. Saaty's [11] groundbreaking work introduced a pairwise comparison theory, harnessing expert judgments to quantify intangible factors. The scale of absolute judgments assesses relative dominance, enabling decision-makers to evaluate complex attributes. Dweiri et al. [12] presented an AHP-based decision support model for supplier selection, focusing on four pivotal criteria: “price, quality, delivery, and service”. By incorporating expert judgments through AHP, the model provides a structured approach to evaluating and ranking potential suppliers. Mohammad Kazem Sayadi et al. [13] advanced the VIKOR method by incorporating interval numbers and decision-maker optimism levels. This enhancement enables effective multi-criteria optimization and conflict resolution. By calculating a ranking index based on closeness to the best idea, the VIKOR method gives a robust framework for evaluating complex alternatives [26].

Chandra et al. [29] formulated a hybrid MCDM integrating AHP-TOPSIS framework. It evaluated AM technologies on economic, social, and environmental criteria. This study ranked the SLS, FDM, and SLA methods on the above-mentioned criteria. Exper surveys and sensitivity analysis were carried out to validate the results. Similarly, Vimal et al. [30] utilised FAHP to compare RP alternatives. The author developed a decision support system for a sustainable manufacturing scenario. A researcher introduced an integrated MCDM approach using multiple tools to support more balanced and consistent decision-making across technical, financial, and operational aspects. Algunaid et al. [31] presented a methodological framework based on DEMATEL, AHP, and TOPSIS. The framework is specially designed to select RP. The study evaluated multiple options across multiple criteria. Sensitivity analysis and a survey were implemented to validate it with real-world RP implementation. D. Ren et al [32] structured an MCDM framework for selecting additive manufacturing (AM) methods. It utilised the AHP-TOPSIS analytical method to rank the available alternatives. Built, Cost, and mechanical properties were the main criteria considered for the study. The model was validated with the case study, proving its applicability in a decision-making scenario in AM. Menekşe, A et al [33] employed hybrid Fuzzy MCDM techniques CRITIC + EDAS with Pythagorean fuzzy logic. It managed the uncertain and subjective judgments. This makes the methodology more robust.

1.4. Process Parameters

Sharanjit Singh et al. [14] conducted a parametric analysis of the laser-sintered polyamide component, concentrating on laser power, scan distance, bed temperature, hatch length, and scan count. The results highlighted the critical role of scan spacing in influencing density and hardness, surpassing the impact of other significant factors**.** K. Chockalingam et al. [14] conducted an in-depth analysis of process parameters impacting part strength in additive manufacturing. Their study focused on layer thickness, post-curing time, and orientation, utilizing the design of experiments to derive empirical relationships and optimize part strength. L. Hitzler et al [16] studied characteristics of Invar 36 components. Components were manufactured by laser powder-bed fusion (LPBF). The study focused on the thermal expansion of material and elastic stiffness. The study considers various temperature ranges. Relationship between processing parameters and temperature-dependent Young’s modulus. It focused on retention of ultra-low thermal expansion up to ~100 °C - key for precision engineering applications. Mohamed et al. [17] applied the design of experiment and the Taguchi design study. The author experimented with PC/ABS instead of using pure ABS alone. This study optimises FDM process parameters. An integrated material study is carried out in this work.

1.5. Inferences from Literature

The rapid prototyping sector faces technological saturation, complicating the selection process [17]. Historically, research has prioritized high-volume manufacturing, neglecting the unique demands of small-scale producers with restricted production runs [18]. The constant influx of innovative materials and processes renders traditional selection frameworks obsolete, underscoring the necessity for adaptable, knowledge-driven approaches to rapid prototyping method selection [20].

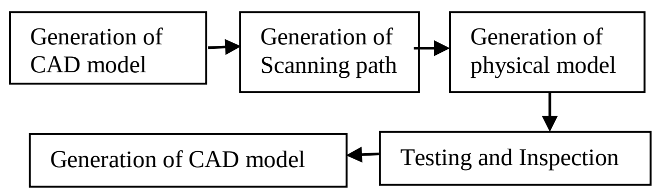

Fig. 3 Steps for prototype manufacturing

Decreased development time and reduction in flaws in design and manufacturing are the main outcomes of RPT. Several challenges in process selection, like expertise, materials, cost, service conditions, and availability, make implementation difficult. This motivates further study in RPT and its effective use in small-scale industries. None of the researchers provided a concrete platform to optimize the RP process selection complexity. Very little emphasis has been given to analytical support for RP process selection. Rapid prototyping methods offer diverse options for product development and modification. However, selecting the correct method is complex and time-consuming due to interconnected factors: quality, part properties, cost, build envelope, and build time. As per the review, very little importance has been given to implementing RP in small-scale industries due to limitations in expertise. Proper process selection criteria have not yet been developed for a particular product. Components with slight variations in specifications were not considered. In adherence to the literature on manufacturing using available RPT methods, no concrete database or predictive model has been presented in research by any of the researchers. For any specific component, available studies have limitations. No broad study or mathematical modeling has been presented previously.

1.6. Real-World Challenges

RP implementation in small-scale industries is facing material limitations, cost overruns, equipment reliability issues, and skill gaps. For developing a functional prototype in the medical device process, the selection becomes too tough. In certain applications of aerospace components, regulatory and certification hurdles make RP implementation very slow.

2. Analytical Methodology

MCDM Techniques play an important role in process selection for specific products with desired attributes. The number of variables with production uncertainty makes it mandatory to implement the analytical study of the different processes and their parameters with the desired attributes of the product. MCDM offers various advantages over actual experimentation, as experimentation involves a loss of resources. Actual experimentation is carried out to find out the considered attributes using direct measurement techniques. These product measurements are placed in a measurement matrix. This methodology helps rank the available RPT methods without complex calculations.

This approach provides concrete analytical support to the ranking procedure between available RPT methods. “Duraform, SLResin, ABSM40, and PC ABS are considered for the manufacturing of the prototype on SLS, SLA, FDM, and 3DP, respectively. The part manufactured with the help of this available RPT method can be used in the sprinkler system head. This system comprises several other parts and assemblies to ensure an effective sprinkling system. The producing part must have the highest tensile strength, surface finishing, geometrical accuracy, and lowest build time, along with cost.

The equipment and instruments used for measuring key product attributes, including surface roughness and tensile strength. The testing procedures followed included the use of a contact-type surface profilometer for surface finish and a universal testing machine (UTM) for tensile testing. The standard protocols referenced during evaluations include ISO 4287 for surface roughness and ASTM D638 for tensile testing of polymer-based samples.

2.1. MCDM Method Selection

The Simple Additive Weighting method was chosen because it is straightforward, easy to apply, and works well when dealing with numerical data. It allows for quick comparison across different alternatives by simply adding up weighted scores, which makes it both practical and efficient. The Weighted Product Method was also included, as it offers a different approach by using multiplication instead of addition. This makes it especially useful when the criteria are expressed as ratios or percentages, such as cost efficiency or build speed. Lastly, we selected VIKOR because it is designed to find a compromise solution in situations where trade-offs exist between conflicting criteria. This is particularly relevant for rapid prototyping, where choosing the best method often involves balancing performance, cost, and material properties.

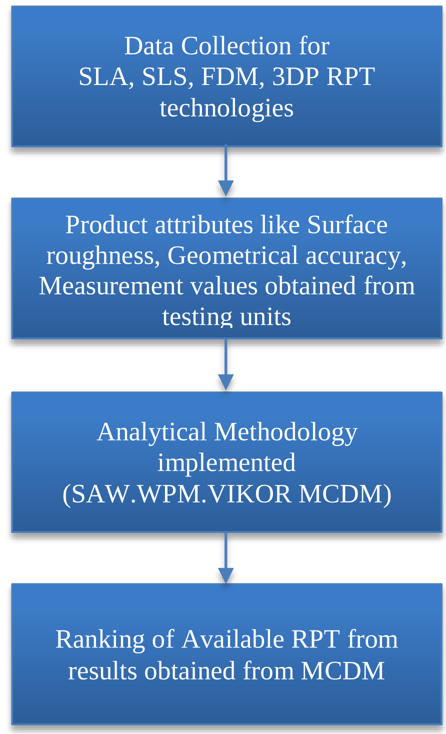

Fig. 4 Methodology for analytical calculation

2.2. Simple Additive Weightage (SAW) [1]

The terms Surface roughness, Geometrical accuracy, Tensile strength, build time, and Cost will be mentioned as SA, GA, TS, BT, and C, respectively, henceforth in the document. A measurement matrix is formed using available measured values from components. Different components were manufactured using stereolithography, specific laser 3D Printing, Sintering, and Fused deposition modelling methods. Surface roughness is measured using a talysurf roughness tester, and values are measured in microns. Geometrical accuracy is considered in mm, tensile strength in MPa, build time in minutes, and cost in rupees. Table 1 shows measurement values obtained from the product.

Table 1. Measurement matrix

	SF	GA	TS	BT	C
SLA	10	0.168	41	185	1100
SLS	21	0.219	42	175	900
3 DP	30	0.41	37	170	930
FDM	31	0.326	33	190	950

After the formulation of the measurement matrix, it is normalized using Equation (1) [23].

$$X\,i,j = \frac{x\ i,j\ min}{Xi,j} \tag{1}$$

To ensure consistent results in multi-criteria decision-making, normalization is a crucial step [28]. By transforming all criteria to a common unit, normalization enables the comparison of different criteria with varying units [29]. This process eliminates the dependency on units, allowing for a more accurate and reliable evaluation of the criteria [30]. As illustrated in Table 2, the normalized values demonstrate the importance of normalization in facilitating a fair and consistent comparison of the criteria.

Table 2. Normalization matrix

	SF	GA	TS	BT	C
SLA	0.9761	1	1	0.91891	0.8181
SLS	1	0.47	0.7671	0.971428	1
3 DP	0.8809	0.333	0.4097	1	0.9677
FDM	0.7857	0.3225	0.5153	0.89473	0.9473

The overall score of an alternative can be calculated using a weighted sum of the normalized scores of each criterion. This can be represented mathematically by Equation (2) [23, 28].

$$P_i = \sum_{j=1}^{m} w_j \left(y_{ij}\right)_{normal} \tag{2}$$

Table 3. Multiplication matrix

	SF	GA	TS	BT	C
SLA	0.3	0.23	0.18	0.11	0.08
SLS	0.1	0.17	0.19	0.12	0.1
3 DP	0.1	0.09	0.16	0.13	0.09
FDM	0.1	0.1	0.14	0.11	0.09

Taking into consideration all relevant attributes, the overall composite score is calculated as shown in Table 4. It provides an overall evaluation of each alternative. Also., It facilitates the ranking of available RPT methods with improved consistency [28-30]**.** It is useful to rank the RPT methods among varying environments. The effective ranking is obtained through this method.

Table 4. Composite score by SAW

	Pi
SLA	0.966754
SLS	0.759391
3 DP	0.605066
FDM	0.591769

2.3. Weighted Point Product Method (WPM) [1, 23]

Using the measurement matrix and normalization matrix, the composite or overall performance score (PSI), Pi of an Ai, is determined by Equation (3) [23].

$$P_i = \prod_{j=1}^{m} \left[\left(y_{ij}\right)_{normal}\right]^{\rightleftarrows w_j} \tag{3}$$

Table 5. Overall performance values of individual attributes

	SF	GA	TS	BT	C
SLA	1	1	0.99	0.98	0.98
SLS	0.77	0.9	1	0.99	1
3 DP	0.68	0.81	0.97	1	0.99
FDM	0.6	0.85	0.95	0.98	0.99

Table 6 gives composite scores by the WPM method. This score is used to find the alternative ranking of the methods.

Table 6. Composite score by WPM

	Pi
SLA	0.964989
SLS	0.722946
3 DP	0.539517
FDM	0.541099

2.4. Compromise Ranking Method (VIKOR) [21, 22]

It concentrates on grading and choosing from a set of alternatives in the light of conflicting limits. The compromise result is an achievable result that's the nearest to the ideal result, and a compromise known as an agreement substantiated by collective concession [20]. Using the following equation, the expectancy of attributes is calculated. All the attributes are scaled down to between 0 and 1.

$$x_{i\rightleftarrows j} = \frac{Max\{y_{i\rightleftarrows j,}i = 1,2,\ldots,n\} - y_{i\rightleftarrows j}}{Max\{y_{i\rightleftarrows j,}i = 1,2,\ldots,n\} - Min\{y_{i\rightleftarrows j,}i = 1,2,\ldots,n\}}$$

Table 7. Expectancy of attributes

	TS	SF	GA	BT	C
SLA	0.111	0	0	0.770	1
SLS	0	0.7731	0.394	0.271	0
FDM	0.555	0.9840	1	0	0.177
3DP	1	1	0.821	1	0.289

Step 1 : Find out the values of E_i & F_i by using the following formulae.

Calculation of Ei,

$$E_i = \sum_{j=1}^{M} \frac{W_j\left[\left(m_{ij}\right)_{max} - \left(m_{ij}\right)\right]}{\left(m_{ij}\right)_{max} - \left(m_{ij}\right)_{min}}$$

Calculation of Fi,

$$F_i = Max\left\{\frac{W_j\left[\left(m_{ij}\right)_{max} - \left(m_{ij}\right)\right]}{\left(m_{ij}\right)_{max} - \left(m_{ij}\right)_{min}}\right\}$$

Table 8 shows calculations for finding E_i and Fi

Table 8. Calculation of E_i and Fi

	TS	SF	GA	BT	C
SLA	0.0211	0	0	0.1001	0.1
SLS	0	0.2706	0.0907	0.0352	0
FDM	0.10554	0.3444	0.23	0	0.0177
3DP	0.19	0.35	0.18884	0.13	0.0289

Table 9. Values of E_i & Fi

RP Process	Ei	Fi
SLA	0.22121	0.1001
SLS	0.39661	0.2706
FDM	0.69769	0.3444
3DP	0.88777	0.35

Step 2: Find the value of Pi

v [(Ei – Ei min) = Pi/ (Ei max – Ei min)] + (1 – v) [(Fi – Fi max) / (Fi max – Fi min)]

Where Ei-max is the max. value of Ei,
Ei-min termed as min. value of Ei,
Fi-max termed as the max. value of Fi,
Fi-min termed as the min. value of Fi
v=0.5.

Table 10. Performance index calculations

E_i		E_i - $E_{i\,min}$	$E_{i\,max}$ - $E_{i\,min}$	(E_i - $E_{i\,min}$) / ($E_{i\,max}$ - $E_{i\,min}$)	V = 0.5
0.22	$E_{i\,Min}$	0	0.66	0	0
0.39		0.17	0.66	0.26	0.13
0.69		0.47	0.66	0.71	0.35
0.88	$E_{i\,Max}$	0.66	0.66	1.00	0.50

Step 3: Keep the alternatives in increasing sequence, in accordance with the values of Pi. Consequently, this process yields three distinct ranking lists.

Table 11. Comparison of performance index

RP Process	Pi	Ei	Fi
SLA	0	0.2212098	0.100
SLS	0.3475454	0.3966123	0.270
FDM	0.7082042	0.6976859	0.344
3DP	1.000055954	0.887774586	0.35

Step 5: Propose as a compromise solution the alternative (p') which is ranked as fair enough by the minimum Q

Table 12. Compromise solution of performance index

RP Process	Pi	Ei	Fi
SLA	0	0.221	0.100
SLS	0.3475	0.396	0.270
FDM	0.7082	0.697	0.344
3DP	1.0000	0.887	0.35

3. Results and Discussions

The novelty of this research lies in providing a concrete and analytical framework for rapid prototyping (RP) method selection, which is notably lacking in existing literature. While several studies discuss RP techniques and their benefits, very few offer a quantitative basis for selecting the most suitable method for a specific application. This study bridges that gap by implementing multi-criteria decision-making (MCDM) methods, SAW, WPM, and VIKOR, to evaluate and rank available RP methods.

The following results were obtained through the application of these methods. For SAW and WPM, the higher overall composite score indicates better suitability of the method, with descending scores representing less suitable alternatives. In contrast, the VIKOR method ranks alternatives in ascending order, where the lowest value suggests the most suitable method.

Analytical calculations were performed using measured data from actual components, and relative performance indices were computed. This approach simplifies the process of selecting the optimal RP method for a given component. Unlike prior studies that rely on qualitative judgment or general suitability charts, this research uses real-time data to generate rankings based on performance indicators such as surface roughness, tensile strength, build time, and cost.

Among the evaluated methods, stereolithography emerged as the most suitable, followed by Selective Laser Sintering, a conclusion supported consistently across all three MCDM techniques. Although these methods are widely used in various industries, their appropriate application to evolving product requirements remains a complex decision-making challenge. The proposed analytical model offers a novel decision-support tool for identifying the most effective RP method in context-specific manufacturing scenarios, particularly where precise component specifications are critical. His study presents a data-driven model using SAW, WPM, and VIKOR for selecting the best RP process, offering a more objective alternative to past qualitative methods. It stands out as one of the few works focused solely on RP selection and is especially useful for small-scale industries with limited expert input.

Table 13. Compromise solution of performance index

RP Process	Pi	Ei	Fi	Ranking
SLA	0	0.2212	0.1001	1
SLS	0.3475	0.3966	0.2706	2
FDM	0.7082	0.6976	0.3444	3
3DP	1.0000	0.8877	0.35	4

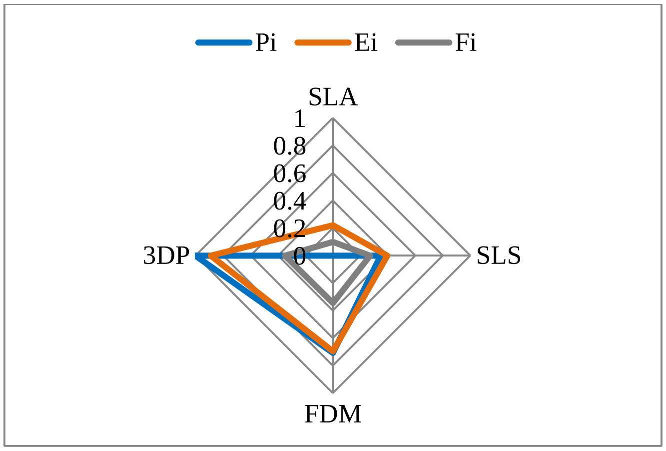

Fig. 5 Compromise solution of performance index

The results show that SLA (Stereolithography) ranks first, with the lowest Fi value of 0.1001. This indicates that SLA is closest to the ideal solution among all the evaluated processes. Its Pi value of 0 suggests that it performs best on at least one of the criteria, while its Ei value of 0.2212 confirms that it stays reasonably far from the worst performance. SLS (Selective Laser Sintering) ranks second, with an Fi of 0.2706. While it is not as optimal as SLA, its performance is balanced and significantly better than the lower-ranked methods. It has moderate values for both Pi and Ei, suggesting consistent results across all criteria. FDM (Fused Deposition Modelling) comes in third, with an Fi of 0.3444. Although FDM is a commonly used and cost-effective technique, its performance in this evaluation is less favourable compared to SLA and SLS, especially in critical areas like precision or surface quality. Finally, 3DP (Three-Dimensional Printing) ranks fourth, with the highest Fi value of 0.35. While its Pi is the maximum (1.0000), indicating poor performance in one or more criteria, its Ei of 0.8877 also shows it is relatively close to the worst-case performance in other aspects.

In summary, SLA emerges as the most suitable RP process based on the VIKOR analysis due to its balanced and superior performance across multiple evaluation parameters. SLS is a viable alternative, while FDM and 3DP may be less favorable for applications where precision, quality, and performance are critical

Table 14. Ranking by SAW and WPM

	Pi (SAW)	Pi (WPM)	Ranking
SLA	0.9667	0.9649	1
SLS	0.7593	0.7229	2
3 DP	0.6050	0.5395	3
FDM	0.5917	0.5410	4

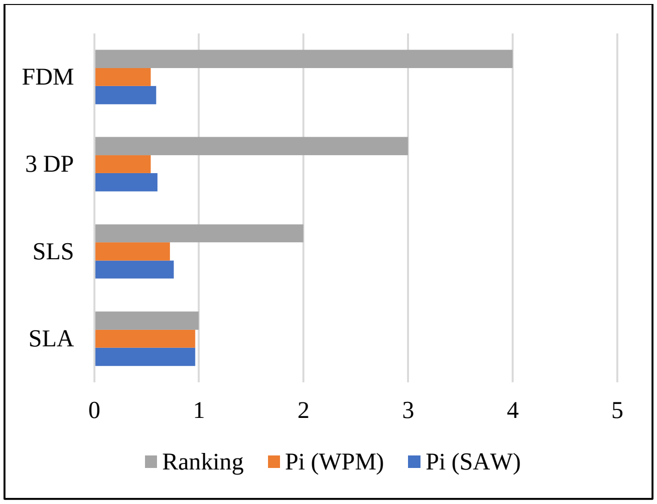

Fig. 6 Ranking of RP methods by MADM techniques

The system having the loftiest value of overall performance or overall composite score is considered to be a stylish, indispensable system. Then SLA has the loftiest composite score and hence the elegant indispensable system.

Whereas it's followed by SLS, 3DP, and FDM while considering the over-said product attributes. The following ranking results were attained using the Simple Additive Method (SAM) and Weighted Point Product Method (WPM), and were

1. The loftiest overall composite score indicates the stylish available choice.
2. Descending order of the overall composite score identifies posterior suitable picks.

4. Conclusion

The findings from this study have direct implications for real-world manufacturing settings, particularly in small and medium-sized enterprises (SMEs) where access to expert knowledge may be limited. By providing a structured, data-driven framework for RP process selection, the model helps decision-makers choose technologies that best align with their production goals—whether it's reducing build time, minimizing cost, or improving surface finish. For example, a firm focused on precision parts may prioritize SLA based on its top ranking, while a cost-sensitive company might still consider FDM, despite its lower overall score.

Future researchers can use multiple digital transformation tools, like laser scanning and 3D mapping, to bring more transparency and speed in prototype development.

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