

A Decision-Making Framework for Selecting Rapid Prototyping Processes in Resource-Constrained Industries Using AHP-GRA

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ABSTRACT

Small-scale industries often hesitate to use Rapid Prototyping (RP) technologies. These technologies come with specific challenges, such as capital investment, expertise, availability, and materials. Traditional machining and forming methods take a lot of time and require significant labor. These limitations reduce the effectiveness of these processes in the fast-paced environment of Industry 4.0. RP provides many advantages that address these issues, as it significantly cuts down product development time, labor needs, and design complexity. However, small-scale industries still face multiple challenges when trying to implement RP. The adoption of RP is often cautious in many industrial settings due to limited access to services, lack of expertise, and high initial costs. To address these challenges, this study presents a systematic research approach that includes an analytical study to help resource-constrained industries choose the best RP process. This work uses a hybrid AHP-GRA model that follows a performance-based and empirically tested method. This approach offers a clear decision-making framework and promotes the use of RP methods among small-scale industries. The findings indicate that SLA (Stereolithography) is the most suitable method, achieving the highest weighted Grey Relational Grade (GRG) of 0.8617. This is followed by SLS (Selective Laser Sintering) with a GRG value of 0.6988, 3DP (3D Printing) with a GRG value of 0.4894, and FDM (Fused Deposition Modeling) with a GRG value of 0.3946.

Keywords-AHP; GRA; decision support system; Rapid Prototyping (RP); process selection; small-scale industries

I. INTRODUCTION

Rapid Prototyping (RP) has been a revolutionary technology in the Industry 4.0 scenario, creating the ability to accelerate product development, validate designs early, and economically prototype them [1-3]. However, the choice of an efficient RP approach is still challenging, especially for SMEs. Some of the key challenges for SMEs include enormous initial capital investment, unavailability of skilled operators, limited availability of uninterrupted material supply, and uncertainty in process performance under resource-limited conditions [4-7].

The absence of a well-defined decision support system that considers technical and economic factors generally amplifies these challenges [8-10]. Some of these Multi-Criteria Decision-Making (MCDM) techniques, such as the Analytical Hierarchy Process (AHP), TOPSIS, and Grey Relational Analysis (GRA) [11-14], have been put forward in the literature; however, their implementation in SMEs is not widespread due to the inadequate utilization of real-world performance data, inadequate weighing of cost-driven factors, and less attention to scenarios under limited resources [15-19].

A. Role of RP in SMEs

RP plays an essential role in assisting Small and Medium Enterprises (SMEs) to reduce time-to-market, shorten product development cycles, and save on initial tooling costs. All SMEs suffer many of the resource implications that accompany any traditional development paradigm (slow development/resource commitment, and high capital), and—unfortunately—as smaller businesses and entities, they typically benefit from neither. This makes RP technologies a feasible alternative as they enable relatively low-cost and short-lead-time production of functional prototypes. These capabilities enable product iteration through customization and concept validation in the early stages of product development. With the good use of RP, SMEs can improve the quality of their products, reduce delivery times, and find new ways to drive innovation without having to rely on an excessive manufacturing infrastructure. RP helps to reduce product development costs. In addition, a smaller quantity of products can be manufactured. This helps SMEs get orders that need a higher development cost if they go for traditional manufacturing processes.

B. Previous Process/Parameter Selection Frameworks

In [8], hybrid MCDM (TOPSIS, SAW, and MABAC) with Taguchi design and MEREC weighting were combined to optimize the EDM parameters in 90CrSi steel. In [9], structured MCDM integrated AHP, ANP, TOPSIS, VIKOR, DEMATEL, and fuzzy Grey methods. In [10], an integrated AHP-TOPSIS framework was proposed, taking into account expert judgment and performance data. In [11], the optimal orientation of parts in additive manufacturing was determined using a DEA-AHP framework. In [12], TOPSIS was employed to evaluate five criteria to obtain the optimal orientation of parts. In [13], a hybrid AHP-GRA technique was used for the selection of suppliers. In [14], a fuzzy AHP-TOPSIS method was proposed to choose an effective supply partner.

C. Applications of AHP-GRA in MCDM

In [15], a novel AHP-GRA hybrid MCDM was proposed to rank the alternatives in additive manufacturing. In [16], an AHP-based combination was used to classify suppliers in refractory material excavations. In [17], AHP-TOPSIS was integrated with WPM and WSM. In the apparel industry, in [18], Fuzzy AHP (FAHP) was combined with a Geographic Information System (GIS) for risk assessment, and in [19], sustainable suppliers were validated using FAHP along with statistical validation. In [20], FAHP was used with PF-VIKOR to prioritize suppliers for the automotive industry during the COVID-19 pandemic. In [21], number theory, AHP, and DEMATEL were combined to address uncertain information. In [22], a useful case on supplier evaluation was presented.

In hybrid MCDM models for the selection of AM processes, sustainable aspects have recently been introduced in the literature [23]. Previous models have integrated environmental factors into RP decision support tools [24]. Other studies combined MCDM methods, such as AHP-TOPSIS and AHP-GRA, expert judgments, and decision rules [25] in similar settings; however, very few studies can be compared. In recent years, several proposals have been made on decision support systems to address the complexity of

machine, material, and process [26]. Decision-maker certainty weighting in improving AM process selection accuracy has been proposed as a new avenue [10].

Although the proposed AHP-GRA framework provides a structured and empirically validated decision-support system [13,15], it has limitations. This method is sensitive to expert input, and its accuracy may vary according to the diversity and expertise level of the respondents [16, 17]. In addition, this model does not directly quantify qualitative adoption barriers, such as operator learning curves, maintenance support, and SC variability [6,7], and its scope is limited to first-order performance parameters. This framework may be expanded in future studies by integrating fuzzy or stochastic weighting approaches to better capture uncertainty and subjective influences [18, 19]. Despite these limitations, this model provides a replicable and practical foundation for SMEs to make informed RP process selection decisions [10]

D. Inferences from the Literature

RP technologies are a highly promising choice, as they have experienced explosive growth, characterized by many features, practices, and limitations, and enable rapid, precise, and diversified production of material products. These qualities make RP an extremely valuable tool in today's Industry 4.0 environment. RP can provide rapid changes and design flexibility. The number of variables in a wide variety of processes and materials complicates the selection of RP. Expertise involvement is greater, as it is extremely difficult to choose the right RP for a specific product, lacking a guide to standardized process selection. Actual issues such as operators' competence, knowledge, economics and availability, and direct and indirect costs incurred, render process selection problematic. All of the above are interconnected, e.g., cost vs quality. Despite such challenges, RP is a very flexible and powerful paradigm for creating prototypes in a wide range of industries.

Common combinations for handling such problems are AHP-TOPSIS, AHP-VIKOR, ANP-Fuzzy TOPSIS, FAHP-DEMATEL, etc. [8-10, 12]. Even today, these models are good enough to provide decision-making assistance; however, their use in uncertain and small dataset contexts and the application of RP for smaller-scale industries pose serious limitations [1, 4, 5]. AHP-TOPSIS has some disadvantages, such as sensitivity to normalization, absence of a mechanism to quantify vagueness, and unbalanced sensitivity to weights. GRA, in turn, deals with limited, vague, or partially unknown data more flexibly, and due to its relational closeness measure, provides more stability to mixed benefit/cost-type criterion data sets.

E. Research Gap and Scope of Study

This study addresses the challenges mentioned above through the development and application of a decision-making method that combines AHP and GRA to select RP processes tailored to the needs of low-resource industries [7, 10, 13]. Four of the most widely used RP methods, namely Stereolithography (SLA), Selective Laser Sintering (SLS), 3D Printing (3DP), and Fused Deposition Modelling (FDM), were the subject of the scope due to their availability, affordability, and applicability in SME manufacturing contexts [1, 5, 27].

Surface Roughness (SR), Geometric Accuracy (GA), Tensile Strength (TS), Build Time (BT), and Cost (C) evaluation criteria were prioritized based on the ISO/ASTM 52902:2019 guidelines [28], which are among the most important factors in the initial stages of product development. Although environmental sustainability and recyclability of materials are a concern [23, 24], industry experts conveyed their relatively secondary impact at the initial stages of process selection [25, 26].

F. Objectives

The aim was to develop an AHP-GRA-based decision model to choose the appropriate AM process considering both benefit- and cost-type criteria based on experimental and expert-based information.

II. METHODOLOGY

The proposed method is a hybrid approach integrating AHP and GRA. This study ranks various available RP processes in priority, with respect to various product characteristics (SR, GA, TS, BT, and C). ISO/ASTM 52902:2019 additive manufacturing test guidelines identify SR, GA, and TS as fundamental measurable quality parameters, and BT and C as the top priority in SMEs embracing RP technologies. These parameters focus on first-tier performance characteristics for small-scale operational environments [1, 28]. These parameters are considered for pairwise comparison (Table I) and normalization (Table II).

The availability of material, environmental concerns, and the energy consumed are some other concern parameters that make process selection more complex. Despite this, industry experience has indicated that these parameters make the process selection more difficult. The degree of the above excluded parameters has slightly less or no impact on process selection. Customers are concerned with the characteristics of the product. TS was established as a "larger-the-better" parameter, and the others as "smaller-the-better" parameters because lower values represent better performance.

Experimentation was performed using calibrated equipment, such as the Mitutoyo SurfTest SJ-210 surface profilometer. The measurement was performed at three equidistant locations in each sample, and the mean value was recorded. TS was measured with a Universal Testing Machine (Instron 3369) with a load cell capacity of 50 kN, according to the ASTM D638 standard for testing polymer samples. GA was measured using a coordinate measuring machine (Hexagon Global Silver) with a probe resolution of 0.001 mm. BT and C were accessed from estimates produced by the slicer and then cross-checked with actual machine run-time and material cost records. This was done to ensure consistency, reproducibility, and correctness in the measurements.

Each test protocol was repeated three times for consistency, and average values were utilized for GRA input. The calculated standard deviations per replicate were within 5%, ensuring the acceptable repeatability levels. These improvements result in the replicability and reliability of data utilized in the model.

A. Analytical Hierarchical Process (AHP)

AHP was chosen because of its systematic method in incorporating expert judgments with proper pairwise comparisons. This method is particularly useful in domains where purely numerical evaluations might be replaced by expert opinions [1-3, 29]. Since AHP is useful in dealing with complicated decision-making contexts or situations where few experts' opinions are yet vital, this makes it suitable for resource-poor/small-scale manufacturing situations [7, 10, 13]. One of the most powerful capabilities of AHP is that it can evaluate the consistency in answers using the Consistency Ratio (CR), making the output priorities more reliable [7, 13, 16, 29]. The experts who participated in a structured evaluation exercise were a panel of RP experts comprising engineers, system operators, and power users with more than 5 years of practical domain experience. Their ratings on Saaty's 1-9 scale were compiled in a pairwise comparison matrix and processed using the geometric mean method. In Table I, each element a_{ij} is the evaluated priority of criterion i over j .

TABLE I. PAIRWISE COMPARISON MATRIX

	SR	A	TS	BT	C
SR	1	4	2	1.5	2
A	0.25	1	2	2	3
TS	0.5	0.5	1	2	3
BT	0.66	0.5	0.5	1	1
C	0.5	0.33	0.33	1	1

Normalization is required to convert all attributes into a comparable scale between 0 and 1, enabling fair evaluation. To derive the normalized matrix, each element was divided by the sum of its respective column using:

$$a_{ij}^{norm} = \frac{a_{ij}}{\sum_{i=1}^n a_{ij}} \quad (1)$$

TABLE II. NORMALIZED PAIRWISE MATRIX

	SR	A	TS	BT	C
SR	0.3428	0.6315	0.3428	0.2	0.2
A	0.0857	0.1578	0.3428	0.2666	0.3
TS	0.1714	0.0789	0.1714	0.2666	0.3
BT	0.2285	0.0789	0.0857	0.1333	0.1
C	0.1714	0.0526	0.0571	0.1333	0.1

Subsequently, the geometric mean of each row in the normalized matrix was computed as:

$$GM_j = \left[\prod_{i=1}^M b_{ij} \right]^{1/M} \quad (2)$$

Relative weights were calculated using,

$$w_j = \frac{GM_j}{\sum_{j=1}^M GM_j} \quad (3)$$

TABLE III. GEOMETRIC MEANS AND CRITERION WEIGHTS

Criteria	GM_j	Weight
SR	0.3122	35 %
GA	0.2060	23 %
TS	0.1793	19 %
BT	0.1155	13 %
Cost	0.0927	10 %

The Consistency Index (CI) and Consistency Ratio (CR) were calculated to ensure the logical consistency of expert judgments. The obtained CR value was less than 0.1, which confirms that the level of consistency is acceptable according to Saaty's criteria. The principal eigenvalue λ_{max} was computed as 5.23. The Consistency Index (CI) was calculated at 0.0575, and with a Random Index (RI) of 1.12 for $n = 5$:

$$CR = \frac{CI}{RI} = \frac{0.0575}{1.12} = 0.051 < 0.1$$

confirming acceptable consistency. Since CR is within an acceptable limit, the weights obtained in AHP are consistent and reliable.

B. Grey Relational Analysis (GRA)

GRA is a well-known and reliable methodological tool for decision making, especially applied to uncertain circumstances or a dataset with gaps [7, 13]. The strength of the system is that it can deal with beneficial and non-beneficial criteria simultaneously, making the proposed method applicable to a composite design problem in real-world engineering where conflicting characteristics exist [4-6]. A nice feature of GRA is that it does not sacrifice accuracy or flexibility for the sake of a streamlined computational structure. It comes up in various fields such as production optimization, manufacturing, systems analysis, etc. [10, 13, 15]. Due to its ability to handle incomplete or imprecise information, it is an attractive option, especially in well-defined application areas where conventional methods are lacking [7, 13].

This study begins with the introduction of the AHP, developed to determine the relative importance of each decision criterion based on expert judgment, which is evidenced as weights operating in a structured pairwise comparison matrix. The GRA process is then fed with the weights generated by AHP to provide a final ranking of the candidate RP methods. This integrated AHP-GRA framework optimizes the best of both objective data evaluation and decisions from experienced experts.

TABLE IV. INITIAL DECISION MATRIX

Process	SR (μm)	GA (mm)	TS (MPa)	BT (min)	C (INR)
SLA	10	0.168	41	185	1100
SLS	21	0.219	42	175	900
3DP	30	0.410	37	170	930
FDM	31	0.326	33	190	950

This table presents the raw performance data of available additive manufacturing processes evaluated across five product-related attributes. Lower values are preferred for all attributes except TS.

1) Normalization of the Decision Matrix

Normalization was performed to eliminate dimensional disparities among criteria and enable comparability. For the higher-the-better attribute (TS), normalization was performed using:

$$x_{i\rightarrow j} = \frac{y_{i\rightarrow j} - \text{Min}\{y_{i\rightarrow j}, i=1,2,\dots,n\}}{\text{Max}\{y_{i\rightarrow j}, i=1,2,\dots,n\} - \text{Min}\{y_{i\rightarrow j}, i=1,2,\dots,n\}} \quad (1)$$

For lower-the-better attributes (SR, GA, BT, and C), normalization was performed using:

$$x_{i\rightarrow j} = \frac{\text{Max}\{y_{i\rightarrow j}, i=1,2,\dots,n\} - y_{i\rightarrow j}}{\text{Max}\{y_{i\rightarrow j}, i=1,2,\dots,n\} - \text{Min}\{y_{i\rightarrow j}, i=1,2,\dots,n\}} \quad (2)$$

TABLE V. NORMALIZATION OF DECISION MATRIX

Process	SR	GA	TS	BT	C
SLA	1.00	1.00	0.80	0.33	0.00
SLS	0.473	0.770	1.00	0.66	1.000
3DP	0.00	0.00	0.40	1.00	0.700
FDM	0.052	0.315	0.00	0.00	0.600

2) Grey Relational Coefficients (GRCs)

The normalized values are used to compute the GRCs, using the following formula, incorporating a distinguishing coefficient $\zeta = 0.5$. This coefficient reflects the closeness of each alternative to the ideal normalized reference (value = 1) for each criterion.

$$\gamma(x_{0j}, x_{ij}) = \frac{\Delta_{min} + \zeta \Delta_{max}}{\Delta_{ij} + \zeta \Delta_{max}} \quad (3)$$

where ζ is the distinguishing coefficient $\zeta \in [0,1]$.

TABLE VI. GREY RELATIONAL COEFFICIENTS (GRCS)

Process	SR	GA	TS	BT	C
SLA	1.000	1.000	0.714	0.428	0.333
SLS	0.486	0.685	1.000	0.600	1.000
3DP	0.333	0.333	0.454	1.000	0.625
FDM	0.344	0.421	0.333	0.333	0.555

3) Grey Relational Grade (GRG) Calculation

The GRG for each alternative is calculated as the weighted sum of its GRCs. The weights are derived from the AHP, representing the relative importance of each attribute as assessed by expert judgment: SR: 0.35, GA: 0.23, TS: 0.19, BT: 0.13, Cost: 0.10.

TABLE VIII. GREY RELATIONAL GRADE (GRG)

Process	GRG Score
SLA	0.8617
SLS	0.6988
3DP	0.4894
FDM	0.3946

Alternatives are ranked based on their GRG scores, with a higher grade indicating greater overall performance compared to the ideal reference across all criteria.

TABLE VII. FINAL GRG AND RANKING

Process	GRG Score	Rank
SLA	0.8617	1
SLS	0.6988	2
3DP	0.4894	3
FDM	0.3946	4

III. RESULTS AND DISCUSSIONS

Figure 1 presents a distribution of the criteria weights calculated with the AHP method. SR scored first, with 35% highlighting its critical importance on the surface integrity, which is a key factor in product quality. This was closely followed by the requirements of GA and TS, with 23% and 19% weightings due to their importance in the performance of parts. In contrast, BT and C (13% and 10%, respectively) were relatively less important, suggesting that these are constraints rather than decision makers in this process.

Stereolithography (SLA) achieved a maximum GRG value of 0.8617, which shows its potential application in high-precision applications. This process has excellent surface finish and dimensional accuracy compared to other RP technologies. Even if the cost of operation is a little higher, the SLA justifies its ranking. Selective Laser Sintering (SLS) followed with a GRG of 0.6988, performing well in terms of mechanical strength and offering a balanced trade-off between cost and build time. 3D Printing (3DP), while offering rapid fabrication, ranked third (GRG = 0.4894) due to compromises in surface quality and precision. Finally, Fused Deposition Modelling (FDM) scored the lowest GRG of 0.3946, largely due to its limitations in accuracy and finish, although it remains a viable option for low-cost, non-critical applications.

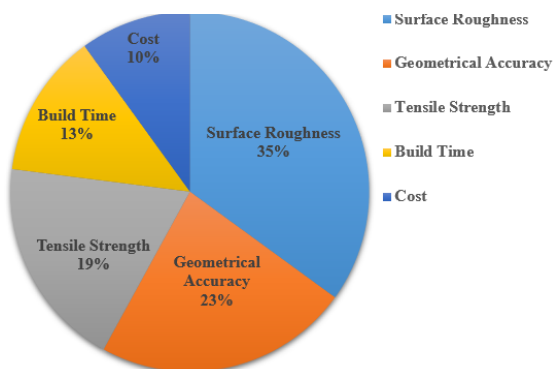


Fig. 1. Weight distribution using AHP

Figure 2 indicates the ranking using GRCs for various available RP processes. The ranking indicates that SLA is the most favorable process for applications where surface quality and dimensional fidelity are paramount. In contrast, SLS may be better suited for applications where mechanical strength and production efficiency take precedence over surface finish quality. This hybrid approach facilitates a comprehensive evaluation that balances quantitative performance metrics with expert-informed judgments on the relative importance of each attribute. As a result, it offers a structured and reliable means of identifying the most appropriate RP method for varying application requirements.

The novelty of this study lies in its integration of AHP and GRA, which offers a structured and expert-informed framework to select an RP process. The hybrid model successfully balances quantitative performance with expert insight, providing practical guidance for small-scale industries operating under resource and knowledge constraints.

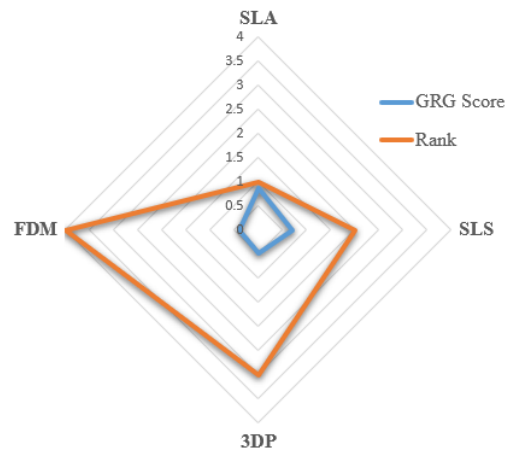


Fig. 2. Ranking by GRA.

IV. CONCLUDING REMARKS

This work offers a solid decision-making tool based on analytical and experimental grounds. The proposed framework helps identify suitable RP technology for products in small-scale industries. This framework can be used in the future, without expertise, for similar-purpose applications. This mitigates the small industry problems related to the implementation of RP processes. The proposed hybrid model combines AHP and GRA, merging expert judgment with quantitative performance measurement for a transparent and trustworthy MCDM process. According to the assessment, SLA is the best option among alternatives, and it has a GRG value of 0.8617, which is better than all the other processes examined. Although the framework seems to have wide applicability in the real world, it demands precise input data and consistency in expert opinions.

A. Future Scope

The proposed model offers a more personalized and organized approach to a variety of prior RP process methods, but it can still be improved and expanded. A system could provide predictive recommendations and streamline decision-making in process selection, thereby increasing accessibility and efficiency for non-expert users.

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