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Grey Relational Analysis in Composites and Process Optimization: A Comprehensive Review

Senthilkumar G [a*]

[a] Lecturer, Department of Mechanical Engineering, Srinivasa Polytechnic College, Pudukkottai District, Tamil Nadu, India.
*Email: sentrm@gmail.com

Abstract
Grey Relational Analysis (GRA) has emerged as a robust multi-criteria decision-making (MCDM) tool for optimizing composite materials and process parameters across diverse engineering domains. This review consolidates and critically analyzes, often in combination with Taguchi design, ANOVA, regression, and artificial neural networks, to enhance mechanical performance in polymer and metal matrix composites. A clear classification between polymer matrix composites-encompassing nanofillers, natural fibers, and hybrid reinforcements-and metal matrix composites is presented to clarify their distinct optimization challenges. Analytical comparisons reveal that GRA effectively captures multi-response interactions in most systems, though its linear assumption limits precision in strongly coupled non-linear parameter spaces. Industrial translation remains constrained by laboratory-scale testing; therefore, future research should integrate techno-economic assessment and life-cycle evaluation to address manufacturability and sustainability. The review highlights cross-study trends, including the dominant influence of surface modification and process parameters on tensile and impact strength improvements. It also emphasizes the need to couple GRA with advanced computational models for non-linear systems. Collectively, these insights establish GRA as a versatile yet evolving optimization framework and outline a roadmap for applying data-driven and cost-sensitive design principles to next-generation composite development.

Keywords: Grey Relational Analysis, ANOVA, Artificial Neural Networks, Polymer Matrix Composites, Mechanical Properties, Metal Matrix Composites.

1. Introduction

Multi-response optimization is a recurring challenge in the field of composite materials and manufacturing. Grey Relational Analysis (GRA) has emerged as a widely adopted multi-criteria decision-making (MCDM) method because it effectively converts multiple performance metrics into a single grey relational grade (GRG), enabling ranking and optimization under multiple, often conflicting, objectives. Across the literature, GRA is frequently combined with experimental design and statistical modeling frameworks-such as the Taguchi method, analysis of variance (ANOVA), regression techniques, artificial neural networks (ANN), and computer-aided engineering (CAE)-to identify significant control factors, enhance prediction accuracy, and validate optimization results.

The studies evaluated in this review collectively demonstrate the breadth of GRA applications in the optimization of mechanical properties, material selection, and process parameters in composite systems. These works span a diverse set of materials, reinforcements, and fabrication strategies. Nanoparticle-reinforced polymer composites and material-selection studies, including the use of alumina nanoparticles and dispersion optimization [1]. Metal matrix composites (MMCs) such as Al–Mg–Si reinforced with palm kernel shell ash, focusing on composition–property modeling [2]. Natural fiber selection and hybrid natural composites, where GRA is used to rank fibers, optimize fiber ratios, and improve mechanical performance [3,4,7,9,10,13,14]. Process-parameter optimization for polymer/composite fabrication, including resin transfer molding and injection molding, where pressure, temperature, fiber layers, and reinforcement percentage are optimized [6,11,12,15]. Structural textiles and auxetic fabrics, focusing on optimizing geometric parameters and tensile properties [5]. Biological and agricultural material property modeling, demonstrating the versatility of GRA beyond engineering materials [8]. Methodological and hybrid modeling contributions, where GRA is combined with Taguchi, ANN, regression, or CAE simulations to enhance predictive power and manage multi-response complexities [6,7,15]. Together, the above studies illustrate the versatility of GRA as an optimization tool across a wide range of composite systems and engineering applications. By synthesizing insights from these diverse studies, this review provides an integrated understanding of how GRA-driven methodologies support material design, process refinement, and performance enhancement.

2. Methodologies and Experimental Design

GRA as the central MCDM tool used to combine tensile, flexural, impact, hardness, and other responses into a single GRG for ranking [1,3-7,9-15]. Taguchi orthogonal arrays (L9, L27, etc.) used in many studies to design experiments economically and systematically [1,6,11-13]. ANOVA and regression analysis used to find statistically significant factors and build predictive mathematical models [2,6,11]. ANN and hybrid GRA–ANN validation, applied where prediction and non-linear modeling were needed [7,10]. CAE / simulation coupled with GRA combines CAE flow simulation with GRA to optimize injection molding conditions with respect to fiber orientation and shear-layer thickness.

Polymer matrix composites (PMCs) comprise systems where organic polymers act as the binding phase reinforced with natural fibers, synthetic fibers, or nanoparticles [1,3-10,13,14]. These works primarily focus on optimizing process variables such as fiber weight fraction, resin content, pressure, and temperature to enhance tensile, flexural, and impact properties. In contrast, metal matrix composites (MMCs), involve metallic matrices such as aluminum alloys reinforced with particulates or ashes. The optimization challenge here lies in achieving uniform dispersion and controlling composition–property relationships [2]. Table 1 provides a concise comparison between PMCs and MMCs, highlighting the difference in matrix type, reinforcement phase, optimization focus, and property outcomes.

Table 1 PMCs and MMCs comparision

Category	Matrix Type	Reinforcement	Optimization Focus	Key Outcome	References
PMCs	Polymer (epoxy, polyester, vinyl ester, etc.)	Natural fibers, nanoparticles	Fiber ratio, surface treatment, process parameters	Improved tensile/flexural strength	1,3-10,13,14
MMCs	Aluminum alloy (Al–Mg–Si)	Palm kernel shell ash (PKSA)	Composition variation, modeling	Improved strength and modeling consistency	2

3. Thematic Analysis of Technical Insights from GRA Studies

3.1. Nanoparticles and polymer nanocomposites

In-situ polymerization of MMA onto alumina nanoparticles improved compatibility, dispersion and mechanical strength. Taguchi-GRA approach identified optimal processing conditions; 2 wt% modified alumina provided notable improvements in impact and tensile strength [1].

3.2. Metal matrix composites and modeling

The Al–Mg–Si–PKSA composite showed mechanical properties that were not monotonically correlated with composition, indicating other influential process/experimental factors. Regression and ANOVA models were used to present mathematical and graphical modeling; GRA helped select optimal compositions while highlighting the need for deeper study of external influencing factors [2].

3.3. Natural-fibre composites and hybridization

Natural fiber selection: GRA effectively ranked candidates for helmet reinforcement (pineapple > bamboo > abaca) [3]. Optimized compositions: Studies found specific weight percentages (e.g., rice husk/straw proportions, sisal/coir ratios, banana/coir formulations) that maximize tensile, flexural and impact strengths [4,7,10,14]. Surface treatments (alkali/NaOH) and fiber hybridization improve interfacial adhesion and mechanical performance; ANN models often validated GRA-derived optima [7,10].

3.4. Process parameter optimization

Number of fiber layers and injection/resin pressure significantly affect tensile/flexural/impact strengths in RTM and injection processes [6,11]. Injection pressure recurrently emerges as a dominant parameter [11]. CAE + GRA: Coupling simulation with GRA allows optimizing for microstructural outcomes like fiber orientation and shear-layer thickness [15].

3.5. Auxetic/woven fabrics & biological stems

Auxetic woven fabrics: Re-entrant honeycomb geometry and small unit cell designs exhibited superior auxeticity and mechanical strength; GRA guided parametric optimization [5]. Tea stem mechanics: GRA-MLR models provided accurate predictive performance for bending and shearing strengths—useful for machinery design [8].

4. Cross-study synthesis — patterns and consensus

GRA reliably aggregates multi-response metrics and, when combined with Taguchi designs, yields efficient experimental paths to find optimal parameter sets across diverse composite systems [1,6,11-13]. Surface treatment, dispersion, and fiber content are repeatedly crucial: whether nano-scale (alumina) or micro-scale (natural fibers), interfacial bonding drives composite performance [1,7,10]. Process parameters often rival material composition in importance: e.g., injection pressure, number of layers, and processing temperature/pressure impact final properties as much as reinforcement percentages [6,11,12]. Hybrid methods (GRA + ANN/CAE/regression) enhance predictive capability and validate experimental optima [7,10,15].

Hybrid natural fiber composites [7,10] demonstrated superior mechanical strength compared to single-fiber systems [3,4], indicating that fiber hybridization and surface modification synergistically improve interfacial adhesion. Similarly, injection pressure emerged as a dominant factor influencing tensile and impact performance in both polymer composites [11] and resin transfer-molded systems [6], underscoring the universal significance of pressure-driven fiber–matrix consolidation. These comparative insights reveal broader design principles-such as optimizing interfacial bonding and controlling process-induced stress distributions-that guide future composite engineering beyond individual case studies.

5. Scalability, Cost, and Life-Cycle Considerations

Although most GRA-based optimization studies have been conducted at laboratory scale, the transition to large-scale manufacturing poses significant challenges. Factors such as cost of raw materials, processing time, energy consumption, and equipment requirements can alter the feasibility of the optimized combinations identified through GRA. For example, hybrid natural fiber composites optimized in small batches [7,10,14] may require different curing cycles or resin formulations when scaled up industrially. Therefore, techno-economic assessment (TEA) and life-cycle costing (LCC) should be integrated with GRA frameworks to evaluate the cost-to-performance ratio and environmental sustainability. Such integration will help industries balance mechanical property enhancement with economic and ecological viability.

6. Limitations

Most works focus on lab-scale parameters without life-cycle analysis or industrial cost modeling. Although several studies consider natural fibers for ecological benefits, few quantify environmental impacts or perform cradle-to-gate analyses. Several studies indicate unexplained variability and call for deeper analysis of additional factors (moisture, processing variability, inter-lab reproducibility). ANN/regression models are typically trained on small datasets from controlled designs; their applicability beyond studied parameter ranges remains untested.

The Taguchi–GRA framework is effective for multi-response optimization, it inherently assumes that factors act independently and linearly. This simplification can limit its accuracy when complex, non-linear multi-factor interactions occur. For instance, the combined effects of fiber treatment, compression pressure, and temperature exhibit non-additive behavior that traditional Taguchi–GRA may not fully capture [7,10]. Moreover, Taguchi orthogonal arrays do not explicitly model interaction terms, which may cause the optimization results to reflect local rather than global optima. To overcome these limitations, future research should integrate Response Surface Methodology (RSM), Genetic Algorithms (GA), or machine-learning-based GRA hybrids that can model curved response surfaces and non-linear dependencies with higher fidelity.

7. Conclusions

This review of studies highlights the extensive and versatile application of Grey Relational Analysis in optimizing composite materials and processing techniques. The findings show that GRA, especially when paired with Taguchi designs, ANOVA, ANN, and CAE, is highly effective for multi-response optimization across diverse composite systems. Key trends include the importance of interfacial engineering for mechanical improvement, the strong influence of process parameters alongside material composition, and the growing value of hybrid computational–experimental approaches. Despite its strengths, current GRA applications remain limited by laboratory-scale data, minimal consideration of manufacturability and cost, and the linear assumptions of Taguchi–GRA frameworks. To advance practical relevance, future work should incorporate larger datasets, nonlinear modeling tools, and techno-economic and environmental assessments. Overall, GRA continues to be a powerful and adaptable tool for guiding material and process optimization in composite engineering.

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Ethical considerations

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Conflict of Interest

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References

1. Saravanan, V., Ramchandran, M., & Murugan, A. (2023). A Study on Alumina Nana Particles Mechanical Properties using the GRA Method. Journal on Materials and its Characterization, 2(2).
2. Oyedeji, E. O., Dauda, M., Yaro, S. A., & Abdulwahab, M. (2022). Mechanical properties optimization and modeling of palm Kernel Shell Ash reinforced Al-Mg-Si composite using grey relational analysis. International Journal of Grey Systems, 2(1), 27-37.
3. Maidin, N. A., Mohd Sapuan, S., Taha, M. M., & Yusoff, M. M. (2022). Material selection of natural fibre using a grey relational analysis (GRA) approach. BioResources, 17(1), 109.
4. Ghalme, S. G. (2021). Improving Mechanical Properties of Rice Husk and Straw Fiber Reinforced Polymer Composite through Reinforcement Optimization. Jordan Journal of Mechanical & Industrial Engineering, 15(5).
5. Zeeshan, M., Ali, M., Riaz, R., Anjum, A. S., Nawab, Y., Qadir, M. B., & Ahmad, S. (2022). Optimizing the auxetic geometry parameters in few yarns based auxetic woven fabrics for enhanced mechanical properties using grey relational analysis. Journal of Natural Fibers, 19(12), 4594-4605.
6. Kopparthi, P. K., Kundavarapu, V. R., Kaki, V. R., & Pathakokila, B. R. (2021). Modeling and multi response optimization of mechanical properties for E-glass/polyester composite using Taguchi-grey relational analysis. Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering, 235(2), 342-350.
7. Sumesh, K. R., & Kanthavel, K. (2022). Optimizing various parameters influencing mechanical properties of banana/coir natural fiber composites using grey relational analysis and artificial neural network models. Journal of Industrial Textiles, 51(4_suppl), 6705S-6727S.
8. Du, Z., Hu, Y., & Buttar, N. A. (2020). Analysis of mechanical properties for tea stem using grey relational analysis coupled with multiple linear regression. Scientia Horticulturae, 260, 108886.
9. Pandya, V. J., & Rathod, P. P. (2020). Optimization of mechanical properties of green composites by gray relational analysis. Materials Today: Proceedings, 27, 19-22.
10. Sumesh, K. R., & Kanthavel, K. (2020). The influence of reinforcement, alkali treatment, compression pressure and temperature in fabrication of sisal/coir/epoxy composites: GRA and ANN prediction. Polymer Bulletin, 77, 4609-4629.
11. Mohamed, S. A. N., Zainudin, E. S., Sapuan, S. M., Deros, M. A. M., & Arifin, A. M. T. (2019). Integration of taguchi-grey relational analysis technique in parameter process optimization for rice husk composite. BioResources, 14(1), 1110-1126.
12. Kumar, B. P., Venkataramaiah, P., & Ganesh, J. S. (2019). Optimization of process parameters in injection moulding of a polymer composite product by using gra. Materials Today: Proceedings, 18, 4637-4647.
13. Navaneethakrishnan, S., & Athijayamani, A. (2015). Taguchi method for optimization of fabrication parameters with mechanical properties in fiber and particulate reinforced composites. International Journal of Plastics Technology, 19(2), 227-240.
14. Chanda, B., Kumar, R., Kumar, K., & Bhowmik, S. (2015). Optimisation of mechanical properties of wood dust-reinforced epoxy composite using grey relational analysis. In Proceedings of Fourth International Conference on Soft Computing for Problem Solving: SocProS 2014, Volume 2 (pp. 13-24). Springer India.
15. Chang, S. H., Hwang, J. R., & Doong, J. L. (2000). Optimization of the injection molding process of short glass fiber reinforced polycarbonate composites using grey relational analysis. Journal of Materials Processing Technology, 97(1-3), 186-193.