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Optimisation of Mechanical Properties on Sunflower Seed Husk-Reinforced Epoxy Composite Using Regression and Grey Relational Analysis

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Abstract

The current research focuses on optimising parameters, namely the mechanical properties of a polymer composite. This composite consists of an epoxy base with particles derived from Sunflower Seed Husks (SSH) used as an additive. To enhance the overall mechanical properties of the polymer composite, the study employs simple linear regression analysis to determine the effect of varying filler content on these properties. Additionally, the grey relational analysis (GRA) technique is used to determine the optimal proportion of SSH filler. Based on the simple linear regression analysis, there is a substantial impact on the mechanical properties and the results of GRA show that Sample ID SSH-0 and SSH-5 exhibits improved mechanical properties.

Keywords: Grey relational analysis, Regression analysis, Mechanical properties, Epoxy & Sunflower seed husk filler

1. Introduction

Composites have acquired augmented importance in present-day materials by virtue of benefits such as their diminished weight, resilience against corrosion, and elevated fatigue potency. The infusion of both natural and synthetic fibers into polymer composites has yielded enhancements in their mechanical and physical characteristics across a spectrum of research initiatives. There's a strong correlation between the experimental and Artificial Neural Network (ANN) data with an error of ±12 percent, while the regression model had a higher error of about 26 percent [1]. Alumina nanoparticles face chemical incompatibility, hindering dispersion and affecting their performance, while Multi-Criteria Decision Making methods were used for selecting optimal nanoparticles to enhance dental mechanical properties [2]. Modeling showed external factors impact Al-Mg-Si-Palm Kernel Shell Ash composite properties. Analysis of Variance (ANOVA) confirmed the model, and property interactions offered a comprehensive composition insight [4]. Natural fibers in cyclist helmets were chosen using GRA, aligning with consumer and environmental criteria. GRA is a practical tool for expert input in material selection. Pineapple ranked highest at 0.5687, followed by bamboo at 0.5678, and abaca at 0.4966

[5]. GRA determined the optimal Rice Husk (RH) and Rice Straw (RS) ratio, enhancing tensile and flexural strength in the polymer composite. Combining GRA with experimental data revealed that adding 2 weight percent RS and 8 weight percent RH fibers to bio epoxy resin significantly improved strength [6]. Zeeshanet al. pioneered 2D woven Auxetic Fabrics (AF) with uniform surfaces to enhance manufacturing efficiency. Optimized AF fabrics have 67.3 percent higher GRA grade and 23 percent greater tensile strength [7]. E-glass/polyester composites were made by varying fiber layers and resin injection pressures in a specialized mould. GRA showed the best tensile, flexural, and impact strengths in the six-layer composites with optimal control parameters [8]. According to GRA analysis, the trial combination comprising 20 weight percent banana, 15 weight percent coir, 3 weight percent NaOH treatment, and 16 MPa compression pressure fared best out of 16 combinations [9]. GRA and Multi-Linear Regression offer a valuable and efficient method for designing appropriate cutting machinery based on the mechanical properties of tea stems [10]. Regression coefficients analyze input parameters (e.g., impingement angle, erodent type, workpiece reinforcement) and erosion loss, quantifying their impact on erosion resistance in nonconductive epoxy composites [11]. GRA ranks mechanical properties based on input variables, identifying the optimal mix for different properties [12]. GRA optimized tensile, flexural, and impact properties using factors such as sisal fiber content, coir fibers, NaOH treatment, and compression pressure. The best results came with 20 percent sisal, 15 percent coir, 5 percent NaOH, and 10 MPa pressure [13]. The optimization process consolidated performance attributes into a single characteristic by considering correlations among temperature, pressure, speed, and cooling time, resulting in improved tensile strength and hardness [14]. The study optimized PMC Cam Bush injection molding by investigating process parameter impacts. Experiments followed the Taguchi L27 Orthogonal Array method, with GRA used to analyze and enhance responses. Findings confirm GRA's effectiveness in achieving optimal parameters [15]. The Taguchi-ANOVA method's effectiveness was confirmed through tests on virgin Polypropylene/Talcum Powder composites using the optimal formula to enhance mechanical properties [16]. The evaluation compared ANN and regression predictions to experimental data. ANN achieved the Coefficient of Determination (R^2) values of about 0.97 for jute and 0.99 for banana fiber composites, while regression had R^2 values of 0.846 for jute and 0.928 for banana fiber composites [17]. Based on our observations, the mechanical properties of Coconut shell powder reinforced vinyl ester composites are significantly affected by fiber content (F value: 10.56) and fiber length (F value: 4.79) [18]. GRA optimization identifies optimal and suboptimal choices. Test run 13 is favored, while test run 3 is less significant. An epoxy composite with 10 percent filler content and 1 mm/min speed performs best, while zero percent filler content and 3 mm/min speed perform least favorably [19]. The Taguchi method relies on measured values, while GRA can use expert opinions, saving costs and labour [20]. This research is focused on studying how the inclusion of SSH filler affects the mechanical properties of epoxy composites. It employs statistical analysis (simple linear regression) and a specific method for dealing with complex and uncertain data (Grey Relational Analysis) to better understand the relationships between the filler and the various mechanical attributes. This research can be valuable for optimizing the use of epoxy composites in applications where these mechanical properties are crucial.

2. Materials and Methods

2.1 Materials and Fabrication

In the synthesis of natural composites, the amalgamation of epoxy resin (LY556 grade), recognized as a thermosetting material, with a low-viscosity hardener (HY951 grade) in a proportion of 10:1 was strategically adopted. This fabrication process involved the implementation of compression moulding employing a mould constructed from mild steel [3,13] and utilizing SSH particles as reinforcement, with varying volume percentages ranging from 5 percent to 50 percent. Test specimens were fabricated in accordance with the relevant ASTM standards, all tests were executed thrice, and the ensuing results are depicted as the average outcomes [3].

2.2 Methodology

2.2.1 Grey Relational Analysis (GRA)

Grey Relational Analysis is a method designed to assess the degree of correlation or similarity among multiple sequences or factors within a system. Originating in the 1980s by Deng Julong [2,14], GRA finds broad application across engineering, economics, management, and various fields, serving to address intricate problem sets. The process involves calculating the deviation sequence, capturing disparities between comparative and reference sequences. Following this, the Grey Relational Coefficient (GRC) is computed to quantify the degree of correlation between these sequences. These GRC values then determine the performance ranking of comparative sequences, contributing to the calculation of the Grey Relational Grade (GRG) as an average GRC value for each sequence. The GRG value, spanning from 0 to 1, reflects the extent of correlation and overall performance, with higher values denoting stronger alignment and improved outcomes [6, 13,14].

Table 1. Simple linear regression model

Description	Equation	Nomenclature
Simple linear regression	y = a + bx	y = represents the dependent variable. x = represents the independent variable. a = is the y-intercept, representing the value of Y when X is 0. b = is the slope of the regression line,indicating the change in y for a one-unit change in x.

2.2.2 Simple Linear Regression Analysis

Simple linear regression is a statistical method used to model and analyse the relationship between two continuous variables: a dependent variable and an independent variable [4]. Table 1. shows the equation for simple linear regression analysis. The goal is to find a linear equation that best describes how changes in the independent variable are associated with changes in the dependent variable. Simple linear regression contains the following:

- Correlation in simple linear regression helps to assess the degree and direction of the linear relationship between the two variables. Pearson correlation is a powerful and widely used measure of linear association between two continuous variables.
- Estimating the coefficients is a fundamental step in simple regression analysis, as they enable us to calculate the SE Coef (Standard Error of Coefficients), T-Value (T-Statistic), P-Value (Probability Value), and VIF (Variance Inflation Factor).
- The model summary is a valuable resource for understanding the quality and significance of a simple linear regression analysis and its ability to explain and predict the dependent variable based on the independent variable. It is often used to communicate the results of the analysis to others and to make informed decisions based on the model's findings.
- ANOVA in simple regression analysis serves as a hypothesis test that evaluates the overall significance of the regression model. It quantifies how much of the variability in the dependent variable can be attributed to the inclusion of the independent variable and provides statistical evidence to determine whether the model has explanatory power. If the ANOVA results are significant, it suggests that the independent variable is a meaningful predictor of the dependent variable, and the regression model is a valuable tool for understanding their relationship.

3 Result and Discussions

3.1 Grey Relational Analysis (GRA)

Grey relational analysis is a statistical technique for multi-objective optimization problems [6]. This technique helps to convert the multi-objective problem into a single objective for all the mechanical properties such as tensile, flexural, compression, hardness and impact strength [13]. The present study utilized the mechanical properties of the SSH filler-reinforced epoxy composite as provided in reference [3]. These composites, denoted as Sample ID SSH-0 to SSH-50, exhibit varying filler concentrations. Experimental results in reference [3] are normalized in the range of 0 to 1 which is shown in Table 2.

Sample ID SSH-0 (Neat Epoxy) displayed exceptional Tensile Strength, Flexural Strength, Compression Strength, and Shore D Hardness, all normalized to 1, indicating robust structural strength. However, its Impact Strength was remarkably low at 0.000, making it highly brittle. Introducing a 5% volume fraction of SSH filler to Sample ID SSH-5 resulted in a slight reduction in Tensile and Flexural Strength compared to SSH-0, suggesting a modest weakening of these properties. Compression Strength and Shore D Hardness remained unchanged, with normalized values of 1.000. Impact Strength improved relative to SSH-0 but remained relatively low. On the other hand, Sample ID SSH-50, with a 50% volume fraction of SSH filler, exhibited a significant decrease in Tensile Strength, Flexural Strength, Compression Strength, and Shore D Hardness (normalized values of 0.000). However, it demonstrated an impressive Impact Strength of 1.000, signifying a substantial enhancement in impact resistance. This gain in impact resistance, however, came at the expense of reduced hardness and structural strength due to the high filler content.

Table 2. Normalized experimental data

Sample ID	**Tensile Strength**	**Flexural Strength**	**Compression Strength**	**Impact Strength**	**Shore D Hardness**
SSH-0	1.000	1.000	1.000	0.000	1.000
SSH-5	0.585	0.709	1.000	0.079	1.000
SSH-10	0.484	0.568	0.824	0.132	1.000
SSH-15	0.364	0.436	0.735	0.238	0.804
SSH-20	0.284	0.336	0.706	0.456	0.784
SSH-25	0.247	0.307	0.559	0.621	0.765
SSH-30	0.215	0.269	0.471	0.798	0.726
SSH-35	0.198	0.207	0.353	0.900	0.647
SSH-40	0.148	0.161	0.265	0.941	0.314
SSH-45	0.069	0.090	0.118	0.990	0.176
SSH-50	0.000	0.000	0.000	1.000	0.000

The GRC values in Table 3 provide valuable insights into the relationship between different samples and their mechanical properties. Notably, Sample ID SSH-0 stands out with the highest GRC values (1) for tensile strength, flexural strength, compression strength, and hardness. This perfect GRC value indicates a strong, direct correlation between SSH-0's composition and these mechanical properties. However, it has a lower GRC value (0.333) for impact strength, suggesting a weaker correlation in this specific property. This implies that the composition of SSH-0 significantly influences the other mechanical properties but has a less pronounced effect on impact strength. In comparison, Sample ID SSH-5 exhibits GRC values slightly lower than SSH-0 across all properties but still relatively high, indicating a substantial correlation between the sample's composition and these mechanical attributes. The GRC value for impact strength in SSH-5 is 0.352, indicating a moderate influence of the composition on impact resistance. Conversely, Sample ID SSH-50 shows GRC values of 0.333 for all properties, signifying a perfect correlation for impact strength, with a GRC value of 1. This means its composition has a direct and strong effect on impact resistance. However, its GRC values for the other mechanical properties are much lower, indicating a weaker correlation in these areas. Consequently, it's clear that the composition of SSH-50 primarily impacts impact strength, while its influence on the other properties is less pronounced.

Table 3.Computed outcome values of the grey relational coefficient and grey relational grade.

Sample ID	GRC					GRG	Rank
	Tensile Strength	Flexural Strength	Compression Strength	Impact Strength	Shore D Hardness		
SSH-0	1.000	1.000	1.000	0.333	1.000	0.394	1
SSH-5	0.546	0.632	1.000	0.352	1.000	0.321	2
SSH-10	0.492	0.536	0.739	0.366	1.000	0.285	3
SSH-15	0.440	0.470	0.654	0.396	0.718	0.244	4
SSH-20	0.411	0.429	0.630	0.479	0.699	0.241	5
SSH-25	0.399	0.419	0.531	0.569	0.680	0.236	6
SSH-30	0.389	0.406	0.486	0.712	0.646	0.240	7
SSH-35	0.384	0.387	0.436	0.833	0.586	0.239	8
SSH-40	0.370	0.374	0.405	0.894	0.421	0.224	9
SSH-45	0.349	0.355	0.362	0.980	0.378	0.220	10
SSH-50	0.333	0.333	0.333	1.000	0.333	0.212	11

The GRG values in Table 3 represent the average Grey Relation Coefficient values across all mechanical properties for each sample. These values help us understand the degree of correlation or similarity between each sample and the reference sample for each mechanical property. Additionally, the samples are ranked based on their GRG values, indicating their overall performance concerning the mechanical properties studied. Sample ID SSH-0, with a GRG value of 0.394, holds the highest ranking (1) in the list. This suggests that neat epoxy (SSH-0) exhibits a higher degree of correlation with the reference sample across all mechanical properties considered. Following Sample ID SSH-0, SSH-5 secures the second position with a slightly lower GRG value of 0.321. This implies that Sample ID SSH-5 exhibits a somewhat weaker correlation with the reference sample across all mechanical properties when compared to SSH-0. It indicates that SSH-5's overall performance in these characteristics is slightly lower than that of SSH-0. At the other end of the spectrum, Sample ID SSH-50 ranks the lowest with a GRG value of 0.212. This suggests that SSH-50 shows a weaker correlation with the reference sample across all mechanical properties, signifying poorer overall performance in these characteristics when compared to both SSH-0 and SSH-5.

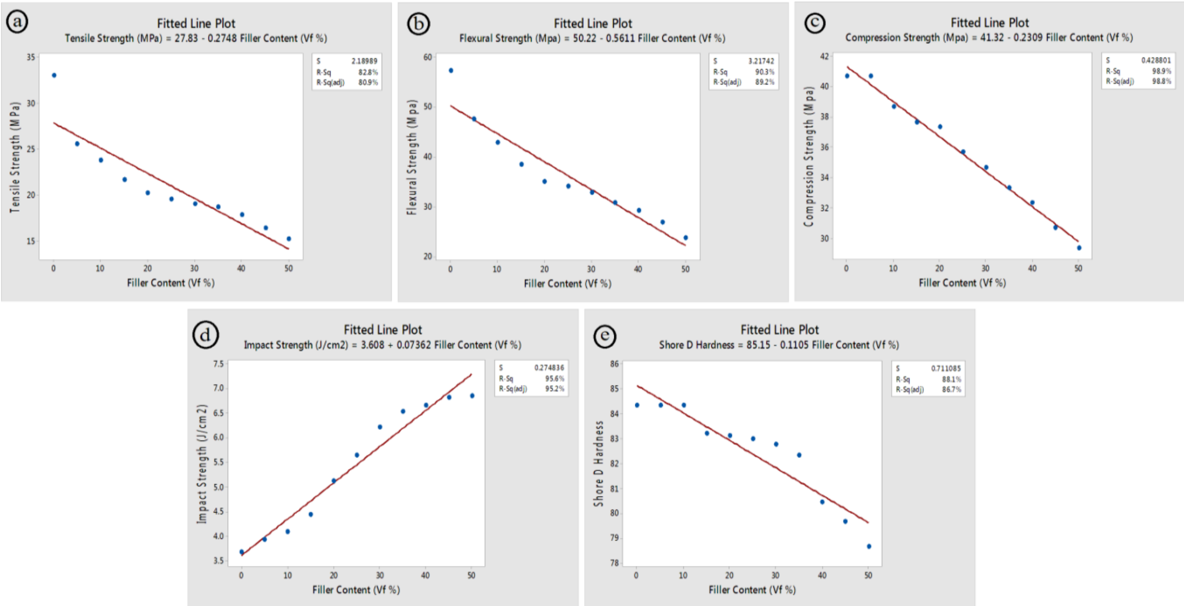

Figure 1 (a-e). Fitted Line Plot for Filler Content vs Tensile, Flexural, Compression, Impact Strength and Hardness of SSH Filler-Reinforced Epoxy Composite.

3.2 Simple Linear Regression Model

Figure 1 (a-e). shows the fitted line plot for filler content versus tensile, flexural, compression, impact strength, and hardness of SSH filler-reinforced epoxy composite. It illustrates the correlations between these variables. The correlations between filler content and the mechanical properties are as follows: -0.910 for tensile strength, -0.950 for flexural strength, -0.994 for compression strength, -0.938 for hardness, and 0.978 for impact strength. These correlations indicate that as filler content increases, there is a strong negative correlation with most mechanical properties (tensile strength, flexural strength, compression strength, and hardness). This is due to weaker interfacial adhesion between the filler and matrix, which increases porosity and causes stress concentration, ultimately leading to a decrease in these properties [3]. In contrast, reinforcing fillers play a vital role in promoting effective load transfer between nearby regions, ensuring a more even distribution of applied forces, particularly when dealing with impact events [3], and there is a strong positive correlation with impact strength.

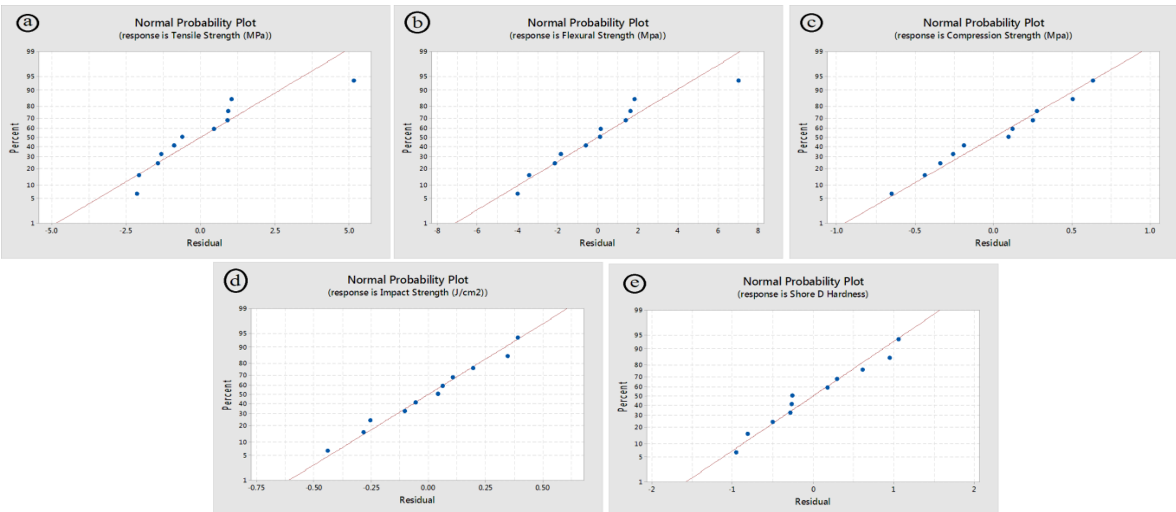

Figure 2 (a-e). Normal Probability Plot for observed values (Tensile, Flexural, Compression, Impact strength and Hardness)

A normal probability plot is a graphical tool used to assess the normality of residuals, which represent the differences between observed values (Tensile, Flexural, Compression, Impact strength, and Hardness) and the values predicted by a statistical model. In Figure 2 (a-e), most of the data points closely follow or cluster around the line of normality. This suggests that the residuals are, for the most part, normally distributed, indicating that the assumption of normality for the residuals in the regression model is being met. However, a few data points deviate from the line of normality, signaling that the assumption of normally distributed residuals is mostly satisfied but there might be some outliers or departures from normality for those specific data points.

Table 4. Model summary of simple linear regression model

Source	S	R-sq (%)	R-sq(adj) (%)	R-sq(pred) (%)
Tensile Strength	2.18989	82.79	80.88	68.05
Flexural Strength	3.21742	90.29	89.21	82.68
Compression Strength	0.428801	98.88	98.76	98.11
Impact Strength	0.274836	95.64	95.15	93.21
Hardness	0.711085	88.06	86.74	80.76

Table 4. represents the standard error of the estimate (S) in a simple linear regression model. This value quantifies the average deviation of the actual data points from the regression line. Impact Strength (0.274836) exhibits lower scatter, indicating a better fit, followed by Compression Strength (0.428801), Hardness (0.711085), Tensile Strength (2.18989), and Flexural Strength (3.21742). From the observation of the S value, it can be inferred that Flexural and Tensile Strength exhibit more scatter, suggesting greater variability in the data and potentially less precision in model predictions. This variability is visually evident in Figure 1&2.

The R-squared values represent the proportion of variability in each mechanical property that can be explained by the respective linear regression models. In Table 4, the linear regression model for compression strength has the highest R-squared value (98.88%), indicating the strongest fit, followed by impact strength (95.64%), flexural strength (90.29%), hardness (88.06%), and, finally, tensile strength (82.79%), which has the weakest fit among the listed properties.

In Table 5.Adjusted Sum of Squares (Adj SS) for Compression Strength is 148.296, with 99% attributed to filler content and model adjustments. Impact Strength's Adj SS is 15.5845, with 96% explained by filler content while accounting for model effects. For Flexural Strength, the Adj SS is 959.09, with 90% associated with filler content and model complexity. Similarly, Hardness has an Adj SS of 38.126, with 88% attributed to filler content and the model. Finally, Tensile Strength's Adj SS is 250.81, with 83% due to filler content and model refinements, reflecting their contributions to overall variation in each property. The 'F-value' is a statistical measure used in analysis of variance (ANOVA) and regression analysis. It assesses the significance of the variation between groups or factors by comparing the variation between groups to the variation within groups. The compression strength model's highest F-Value (797.52) underscores its exceptional significance, while the lowest F-Value for tensile strength (43.30) suggests comparatively less explanatory power. The regression models for various mechanical properties exhibit P-Values of 0.000, indicating high statistical significance. With P-Values below 0.05, the null hypothesis is rejected [6], signifying significant differences between the variables, this indicates that the tensile, flexural, compression strength and hardness of the material is diminished by the incorporation of fillers [3].

In Table 6, there are distinct relationships between the independent variables and the dependent variable. Tensile, Flexural, Compression strength, and Hardness all exhibit negative Coefficients (Coef) -0.2748, -0.5611, -0.23092 & -0.1105; and T-values -6.58, -9.15, -28.24 & -8.15 for the Independent Variable. This suggests statistically significant negative associations; increases in these independent variables correspond to decreases in

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the dependent variable. Conversely, Impact strength stands out with positive measures, indicating a positive relationship with the independent variable. Impact Strength (0.155), Compression Strength (0.242), and Hardness (0.401) have the most precise coefficient estimates with the smallest Standard Errors (SE). Tensile Strength follows with a moderately small SE Coef (1.24), and Flexural Strength exhibits the largest SE Coef (1.81) among the properties, suggesting potentially less precise coefficient estimates in its regression model. The Variance Inflation Factor (VIF) values of 1 for these mechanical properties suggest that there is no excessive correlation or redundancy among them. This is a positive sign for regression models because it indicates that each mechanical property can be independently influenced by the filler content without interference from multicollinearity issues. As a result, using filler content as an independent variable in the regression models is not only reliable but also enhances the accuracy of predicting these mechanical properties. It allows for a more precise and meaningful analysis of how changes in filler content impact each mechanical property separately.

Table 5. Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Tensile strength					
Regression	1	207.65	207.653	43.30	0.000
Filler Content (Vf %)	1	207.65	207.653	43.30	0.000
Error	9	43.16	4.796		
Total	10	250.81			
Flexural strength					
Regression	1	865.93	865.93	83.65	0.000
Filler Content (Vf %)	1	865.93	865.93	83.65	0.000
Error	9	93.17	10.35		
Total	10	959.09			
Compression strength					
Regression	1	146.641	146.641	797.52	0.000
Filler Content (Vf %)	1	146.641	146.641	797.52	0.000
Error	9	1.655	0.184		
Total	10	148.296			
Impact strength					
Regression	1	14.9047	14.9047	197.32	0.000
Filler Content (Vf %)	1	14.9047	14.9047	197.32	0.000
Error	9	0.6798	0.0755		
Total	10	15.5845			
Hardness					
Regression	1	33.575	33.5749	66.40	0.000
Filler Content (Vf %)	1	33.575	33.5749	66.40	0.000
Error	9	4.551	0.5056		

Total	10	38.126			

Table 6. Coefficients in simple linear regression model

Term	Coef	SE Coef	T-Value	P-Value	VIF
Tensile strength					
Constant	27.83	1.24	22.53	0.000	
Filler Content (Vf %)	-0.2748	0.0418	-6.58	0.000	1.00
Flexural strength					
Constant	50.22	1.81	27.67	0.000	
Filler Content (Vf %)	-0.5611	0.0614	-9.15	0.000	1.00
Compression strength					
Constant	41.319	0.242	170.83	0.000	
Filler Content (Vf %)	-0.23092	0.00818	-28.24	0.000	1.00
Impact strength					
Constant	3.608	0.155	23.27	0.000	
Filler Content (Vf %)	0.07362	0.00524	14.05	0.000	1.00
Hardness					
Constant	85.146	0.401	212.28	0.000	
Filler Content (Vf %)	-0.1105	0.0136	-8.15	0.000	1.00

4 Conclusions

The Simple Linear Regression Analysis and Grey Relational Analysis have been effectively employed to evaluate the mechanical properties of Sunflower Seed Husk filler-reinforced epoxy composites. This study, represented by Sample IDs SSH-0 to SSH-50, has revealed trade-offs between static and impact strength properties.

- Simple linear regression analysis indicates that filler content strongly influences the mechanical properties of the material. Tensile strength, flexural strength, compression strength, and hardness all decrease as filler content increases, while impact strength increases with higher filler content.
- In Grey Relational Analysis, GRG results reveal that filler content significantly influences the mechanical properties studied, with SSH-0 showing the most favorable characteristics, followed by SSH-5 and so on in descending order.
- Further research can focus on fine-tuning the filler content to achieve a balance between static and impact strength properties. One promising avenue could involve reducing the filler size to less than 50 microns and conducting similar experiments to find the optimum composition that offers the best combination of mechanical properties. This targeted approach may help in optimizing the material for specific applications and performance requirements, as well as shedding light on the effects of filler size on mechanical properties.

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