ABSTRACT

Hybrid natural fibre polymer composites have attracted significant attention from the research community owing to their better mechanical properties and eco-friendly nature as compared to conventional materials. Abaca, in particular, has shown tremendous potential for its suitability in structural applications. This present work deals with the mechanical characterization and modelling of hybrid abaca-epoxy composites with red mud as a filler. Hybrid composites were prepared by the hand lay-up technique; preliminary experiments involving banana and sisal were also performed to understand the composite fabrication procedure. Experiments for the primary study were designed based on a full factorial method having three control parameters: weight percentage of abaca (2.6, 5.26, and 7.9 wt%), weight percentage of red mud (4, 8, and 12 wt%), and particle size of red mud (68, 82, and 98 mm). The flexural and impact strengths of the composites were evaluated. To further analyze the dataset, find the optimized parameter values, and gather different data insights regarding the input and output parameters, three optimization algorithms—Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), and Differential Evolution (DE)—were employed. This study provides a comprehensive analysis of the composite's mechanical behavior and identifies the optimal formulation for improved performance through a comparative algorithmic approach.

Keywords: Hybrid Composites, Natural Fibre Composites, Abaca, Epoxy, Red Mud, Mechanical Properties, Flexural Strength, Impact Strength, Full Factorial Design, Optimization, Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), Differential Evolution (DE), Hand Lay-up.

TABLE OF CONTENTS	PAGE NUMBER
Declaration	2
Certificate	3
Abstract	4
Acknowledgement	5
List of Figure	7
List of Tables	7
List of Acronyms	7
Introduction	8
Review of literature	10
Problem Definition and Objective	13
Methodology	14
Results and Discussion	19
Conclusion	30
References	31

LIST OF ACRONYMS

GA	Genetic Algorithm
DE	Differential Evolution
GWO	Grey Wolf Optimization Algorithm
RSM	Response Surface Methodology

LIST OF TABLES

Table No	Description	Page No
4.1	Experimental Dataset	14
5.1	Performance Matrix Evaluation	29

LIST OF FIGURES

Figure No	Description	Page No
4.1	GA Flow chart	16
4.2	DE Flow Chart	17
4.3	GWO Flow Chart	18
5.1	Input histogram of Experimental data	19
5.2	Output histogram of Experimental data	20
5.3	Output histogram of Predicted data (GA)	20
5.4	Box Plot of GA	21
5.5	Scatter Plot of GA	22
5.6	Output histogram of Predicted data (DE)	23
5.7	Box Plot of DE	24
5.8	Scatter Plot of DE	25
5.9	Output histogram of Predicted data (GWO)	26
5.10	Box Plot of GWO	27
5.11	Scatter Plot of DE	28

CHAPTER 1
Introduction

BACKGROUND:

There is a growing global demand for materials that are not only mechanically robust but also environmentally sustainable. Conventional polymer composites, often reinforced with synthetic fibres such as glass or carbon, have significant environmental drawbacks, including high energy consumption during production, non-biodegradability, and challenges in disposal. This has driven the research community to explore "green" alternatives.Natural Fibre Polymer Composites (NFPCs) have emerged as a highly promising solution. These materials leverage inexpensive, renewable, and biodegradable natural fibres (like jute, sisal, banana, and coir) as reinforcement in a polymer matrix.Abaca fibre, in particular, is a strong candidate for structural applications.To further enhance the properties of these composites and reduce costs, researchers often incorporate fillers. A particularly innovative approach is the use of industrial waste products as fillers. Red mud, a hazardous alkaline waste generated during alumina production from bauxite ore, poses a significant global disposal problem. Finding a large-scale, value-added application for red mud is a critical environmental goal. Incorporating this waste material into a composite could simultaneously solve a disposal issue and potentially improve the composite's mechanical, thermal, or wear properties.This work explores the concept of using red mud as a filler within an abaca-epoxy composite. This hybrid approach aims to create a value-added material while simultaneously addressing a critical environmental waste problem. However, the final mechanical properties, such as flexural and impact strength, are highly dependent on the complex interaction between the component ratios (abaca wt%, red mud wt%) and the filler's particle size.This study seeks to characterize these effects and apply optimization algorithms to identify the ideal formulation for suitable mechanical performance.

PROPOSED SOLUTION:

This study proposes using advanced heuristic algorithms—namely Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), and Differential Evolution (DE)—to optimize the mechanical properties (flexural and impact strength) of the abaca–red mud–epoxy composite. Unlike traditional statistical models (RSM/ANOVA), which can get limited to finding a local optimum, these advanced computational techniques are better equipped to analyze the complex dataset. They can navigate non-linear interactions to identify the true global optimum—the best possible material formulation. The performance of the solutions derived from GA, GWO, and DE will be comparatively analyzed and validated against traditional methods.

PROBLEM STATEMENT:

Traditional statistical methods like ANOVA and RSM, while useful for regression modeling, are often limited in capturing the complex, non-linear interactions present in advanced material systems. Their reliance on polynomial models can lead to optimizations that find only a local optimum rather than the true global optimum.Furthermore, a specific knowledge gap exists in the literature regarding the synergistic effect of combining abaca fibre and red mud filler in a hybrid composite. This study addresses both challenges. It introduces advanced heuristic optimization algorithms to move beyond the limitations of traditional models. These computational techniques are better equipped to analyze the complex dataset and identify the true optimal formulation for this composite material.

CHAPTER 2
Review of Literature

Anand et al[1] optimized coir–PVC composites by combining RSM with three algorithms: Particle Swarm Optimization (PSO), Dragonfly Optimization (DFO), and Crow Search Algorithm (CSA). They focused on fibre content, size, and treatment to improve thermal performance. The CSA provided the best-optimized result (0.801 W/mK) with the lowest error. In comparison, DFO was consistent, and PSO was fast but less accurate. The study validated that optimized composites are well-suited for eco-friendly industrial applications.Agnivesh Kumar Sinha et al[2] investigated the effect of adding banana fiber reinforcement to an epoxy matrix. Their findings indicated that the inclusion of banana fiber improves both the mechanical strength and thermal stability of the resulting composite. The study emphasized a critical factor: an optimal fiber content exists to enhance impact and tensile properties. Adding fiber beyond this optimal threshold was found to be detrimental, reducing the composite's overall performance. They concluded that these lightweight and eco-friendly materials are viable alternatives for applications in the automotive and construction industries.Ikechukwu G. Chibueze et al[3] applied fuzzy logic models to predict the mechanical properties of sponge gourd–bagasse hybrid composites. Their models demonstrated high accuracy, showing a strong correlation with experimental results. For optimization, they employed a modified desirability function combined with Particle Swarm Optimization (PSO), as well as the Non-dominated Sorting Genetic Algorithm II (NSGA-II). These methods successfully improved the multi-objective optimization, achieving higher desirability values than unmodified approaches. The study concluded that this integrated AI-based framework serves as a reliable tool for designing sustainable composites with a balanced mix of properties, including strength, stiffness, hardness, and elongation.

Ramraji Kirubakaran et al[4]. investigated the properties of composites using rice husk fiber with nano hexagonal Boron Nitride (nano h-BN) as a filler. Their results indicated this combination yielded the best performance, achieving the highest thermal conductivity (1.01 W/m-K) and the highest electrical resistance (346.91 GΩ). The study concluded that nano h-BN fillers significantly enhance the thermal conductivity and insulation properties of the composite, while also reducing its dielectric constant.Shenbaga Velu Pitchumani et al[5] focused on the optimization of Coir Fibre-Reinforced PVC Composites (CFRC). They demonstrated that the mechanical, thermal, and electrical properties of these composites could be significantly improved by optimizing the fibre content, particle size, and chemical treatment. Their study included a comparative analysis of three algorithms: Particle Swarm Optimization (PSO), Dragonfly Optimization (DFO), and Sparrow Search Optimization (SSO). Among these, the DFO method was identified as the best performer, showing higher accuracy (with R^2 values up to 0.95) and greater robustness in predicting the composite's strength. The authors concluded that the optimized composites show strong potential for practical use in electrical and electronic applications due to their well-balanced strength, insulation, and heat dissipation properties.Gopalan Venkatachalam et al. [6] conducted an optimization study on composites containing fly ash, sugarcane fiber, and Carbon Nanotubes (CNTs).

The optimal mix was found to be 0.2 wt.% fly ash, 2 wt.% sugarcane fiber, and approximately 0.4 wt.% CNTs, which achieved the best balance of yield strength, tensile strength, and Young's modulus. Analyzing the material contributions, they noted that sugarcane fiber primarily improved stiffness and yield strength, while CNTs significantly enhanced tensile strength. The use of fly ash was limited due to disposal challenges. For the optimization process, the Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) was used. It proved highly efficient and reliable in identifying optimal material combinations, outperforming traditional Response Surface Methodology (RSM) approaches.Vimalanand Suthenthiraveerappa et al [7] investigated hybrid basalt/jute fiber composites, noting that their strength and energy absorption are significantly affected by process parameters. Using a Taguchi–Grey relational analysis, they identified the optimal conditions for fabrication as 1 wt% basalt, 40 minutes of sonication, and a temperature of 70°C. Microstructural analysis (via microscopy) revealed a strong bond between the basalt and jute fibers. However, the study also observed weak adhesion between the jute fibers and the epoxy matrix, a factor that influenced the overall composite behavior.Shenbaga Velu Pitchumani et al. [8] optimized a hybrid composite and found that the best mechanical and vibration performance was achieved with a composition of 1% Carbon Nanotubes (CNTs), 6% banana fibre, and epoxy resin. This optimal hybrid demonstrated superior tensile strength, impact resistance, and natural frequency compared to other combinations. The study utilized Taguchi–Grey relational analysis as the optimization method, which effectively identified the most influential factors, revealing that the resin type had the highest impact on the results.Mohamad Zaki Hassana et al. [9] explored the use of banana pseudo-stem fibers as an eco-friendly, low-cost reinforcement for epoxy composites. Their work identified fiber length, NaOH (alkali) treatment, and fiber loading as the most significant factors affecting the composite's tensile strength. By applying optimization, they determined the optimal conditions to be a fiber length of 3.25 mm, NaOH concentration of 5.45%, and a fiber loading of 29.86%, which successfully increased the tensile strength by 22%.Hessameddin Yaghoobi et al. [10] studied the effects of kenaf fiber loading, fiber length, and a PP-g-MA compatibilizer on composite properties. They found that tensile strength and modulus were significantly improved, with optimal properties achieved at high fiber loading and high compatibilizer content. Using a Box-Behnken design and Response Surface Methodology (RSM), they developed an accurate quadratic regression model for prediction and optimization. The study also confirmed via SEM that the PP-g-MA compatibilizer enhanced the interfacial adhesion between the kenaf fibers and the matrix, leading to an improved composite morphology.

Jun Hui Tam et al. [11] developed a hybrid GA-ACO-PSO algorithm to identify the elastic properties of composite materials. This hybrid approach demonstrated higher accuracy and repeatability (with absolute percentage errors below 2%) compared to conventional algorithms. The method was also found to be robust, reliably identifying material properties even when measurement errors were present. The authors concluded that the proposed hybrid algorithm effectively balances the strengths of GA, ACO, and

PSO, resulting in an improved convergence rate and more reliable solutions for inverse material identification tasks.Gunyong Hwang et al. [14] employed a Genetic Algorithm (GA) combined with a micromechanics model to optimize the design of woven fabric composites, specifically focusing on maximizing the elastic modulus. Their study established a clear link between geometry and properties: composites with a large strand volume, wide/thick cross-sections, and low waviness exhibited a better in-plane modulus. Conversely, high waviness enhanced the out-of-plane modulus. The authors concluded that these results provide a design basis for tailoring woven fabric composites for specific uses in aerospace, automotive, and sports applications.Yan Wu, Bin Wang et al. [15] reviewed the application of computational methods in composite material design. They concluded that bio-inspired optimization algorithms are highly effective for optimizing the mechanical properties of these materials. Furthermore, they noted that incorporating neural network models significantly improves the prediction accuracy for material performance. Their overall finding was that combining optimization techniques with AI provides a synergistic effect, greatly enhancing the efficiency of the material design process.

CHAPTER 3
Problem definitions and objectives

PROBLEMDEFINITION:

This research addresses a twofold problem: a methodological limitation in traditional modeling and a material knowledge gap. Standard statistical methods like ANOVA and RSM are often limited to finding local optimums, as their polynomial models fail to capture the complex, non-linear interactions within advanced composites. This is coupled with a specific lack of scientific data on the synergistic effects of combining abaca fibre and red mud filler. It is currently unknown how these two materials interact to influence the final mechanical properties, a gap this study aims to fill by using advanced computational optimization techniques better suited for identifying the true global optimum.

OBJECTIVE:

1. To employ advanced heuristic algorithms—namely Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), and Differential Evolution (DE)—to optimize the mechanical properties (flexural strength and impact strength) of the abaca–red mud–epoxy composite.
2. To utilize these computational techniques to navigate the complex, non-linear interactions within the experimental dataset, overcoming the limitations of traditional models (like RSM/ANOVA) to find the true global optimum formulation.
3. To conduct a comparative analysis of the solutions derived from GA, GWO, and DE to evaluate their respective performance and efficiency in solving this materials optimization problem.
4. To validate the computational findings and demonstrate the superior optimization capabilities of these heuristic methods compared to traditional statistical approaches.

CHAPTER 4

Methodology

An hybrid ABACA reinforced polymer composite using RSM was constructed to determine the flexural and impact strength. The below table was refered from Sinha et al[2].

Table 4.1 Experimental Dataset

S.no	A (Wt.% of ABACA fibre)	B (Wt.% of Redmud)	C (Particle size of Redmud)	F (Flexural strength) MPa	I (Impact strength) Joule/meter
1	2.6	4	68	41.55	30.83
2	2.6	4	82	40.56	30.1
3	2.6	4	98	38.29	28.56
4	2.6	8	68	47.9	32.91
5	2.6	8	82	46.62	32.31
6	2.6	8	98	44.29	32.08
7	2.6	12	68	50.29	34.18
8	2.6	12	82	48.89	33.95
9	2.6	12	98	48.34	33.72
10	5.26	4	68	36.54	33.7
11	5.26	4	82	35.46	32.9
12	5.26	4	98	32.28	30.4
13	5.26	8	68	36.25	40.95
14	5.26	8	82	34.35	39.89
15	5.26	8	98	35.94	36.19
16	5.26	12	68	36.89	42.68
17	5.26	12	82	35.51	41.07
18	5.26	12	98	35.43	40.9
19	7.9	4	68	40.25	41.96
20	7.9	4	82	38.73	41.08
21	7.9	4	98	38.09	39.59
22	7.9	8	68	43.78	42.62
23	7.9	8	82	41.31	40.54
24	7.9	8	98	41.22	39.05
25	7.9	12	68	45.86	41.5
26	7.9	12	82	43.46	41.5
27	7.9	12	98	40.6	37.92

4.2 **Genetic Algorithm (GA)**

Genetic Algorithm is an optimization technique inspired by Darwin's theory of natural evolution. It works by evolving a population of solutions through a process of selection, crossover, and mutation. Over successive generations, the population "evolves" toward the best (optimal) solution.

Functions of GA:

- Selection – Chooses the fittest individuals from the population for reproduction.
- Crossover (Recombination) – Combines two parent solutions to form new offspring.
- Mutation – Introduces small random changes to maintain diversity and avoid local minima.
- Fitness Evaluation – Measures how good a solution is with respect to the objective function.
- Replacement – Forms the next generation by replacing weaker solutions with stronger ones.

The Genetic Algorithm (GA) flow chart in Figure 4.2.1 outlines the steps for optimizing a solution using evolutionary principles. The process starts by randomly initializing a population within defined bounds and evaluating fitness based on *flexural* and *impact strength*. The population is sorted by fitness, and the best solution is preserved through elitism. New individuals are generated using selection (tournament method), crossover (probability 0.8), and mutation (probability 0.1). Offspring are adjusted to stay within bounds and added to form the new population, which replaces the old one in each generation. After several generations, the algorithm returns the best solution (A, B, C) and their predicted strengths.

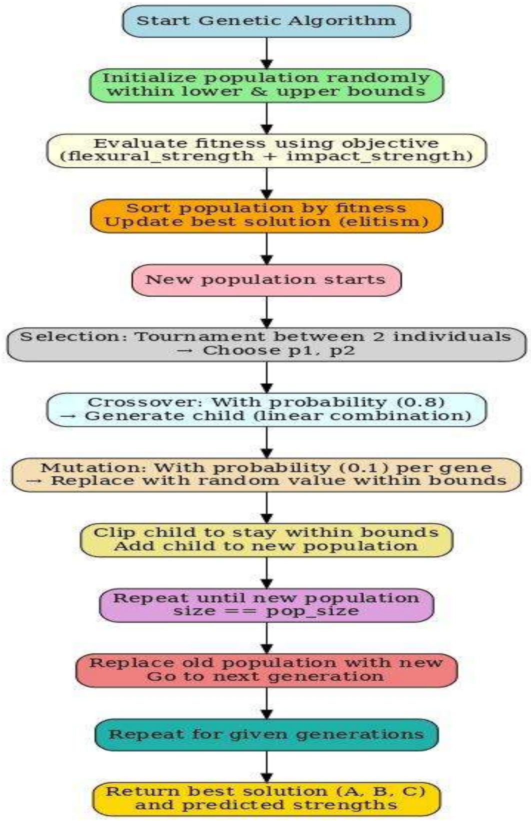


Figure 4.1 Pseudo Code using GA for optimization

4.3 Differential Evolution Algorithm (DE):

Differential Evolution is a population-based optimization algorithm used for solving complex continuous optimization problems. It operates by iteratively improving a population of candidate solutions through mutation, crossover, and selection. DE is known for its simplicity, efficiency, and strong global search capability.

Functions of DE:

- Initialization – Generates an initial population of random candidate solutions within defined bounds.
- Mutation – Creates a mutant vector by adding the weighted difference between two population vectors to a third vector.
- Crossover (Recombination) – Combines the mutant vector with a target vector to produce a trial vector, introducing variation.
- Selection – Compares the trial vector with the target vector and retains the one with better fitness for the next generation.
- Iteration (Evolution) – Repeats the process until a stopping criterion (e.g., maximum generations or convergence) is met, leading to the optimal solution.

The Differential Evolution (DE) flow chart shown in Figure 4.3.1 depicts the optimization process based on population evolution. It begins by randomly initializing a population within the given bounds, followed by evaluating the fitness of everyone using an objective function. The population is then sorted by fitness, and the best solution is stored. A new generation is created through mutation, crossover, and selection. During mutation, three distinct vectors are chosen to generate a mutant vector using a weighted difference. In the crossover step, elements from the mutant and target vectors are combined based on a crossover rate (CR). Finally, selection replaces the target vector with the mutant if it shows improved fitness. This process is repeated for all individuals until the optimal solution is obtained.

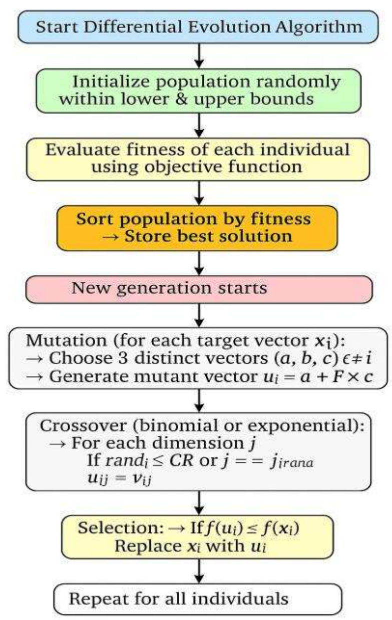


Figure 4.2 Pseudo Code using DE for optimization

4.4 Gray Wolf Optimization (GWO)

Gray Wolf Optimization is a nature-inspired metaheuristic algorithm that mimics the social hierarchy and hunting behavior of gray wolves in the wild. It is primarily used for solving complex optimization problems by balancing exploration and exploitation effectively.

Functions of GWO:

- Initialization – Generates an initial population of gray wolves (candidate solutions) randomly within the search space.

- Hierarchy Formation – Assigns leadership roles: alpha (best solution), beta (second best), delta (third best), and omega (remaining wolves).
- Encircling Prey – Wolves update their positions by surrounding the prey (optimal solution) based on alpha, beta, and delta guidance.
- Hunting – Wolves follow the top three leaders to search for prey, guiding the population toward promising regions of the search space.
- Attacking (Convergence) – As iterations progress, the wolves close in on the prey, refining the solutions and converging to the global optimum.

The Grey Wolf Optimization (GWO) flow chart shown in Figure 4.4.1 illustrates the step-by-step process of simulating grey wolf leadership and hunting behavior for optimization. The algorithm begins by randomly initializing a population within defined bounds, followed by evaluating the fitness of everyone using an objective function. The population is then sorted by fitness, and the best solutions representing the alpha (α), beta (β), and delta (δ) wolves are stored. A new generation starts where the positions and fitness of these three leading wolves are used to guide the mutation and position update of the rest of the population. Everyone's position is updated based on the influence of α, β, and δ, simulating the hunting mechanism of wolves encircling prey. The new fitness values are then evaluated, and the process continues until the termination condition is met, resulting in the optimal solution.

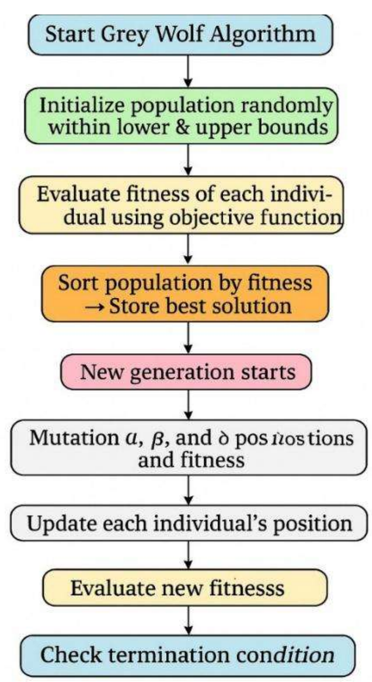
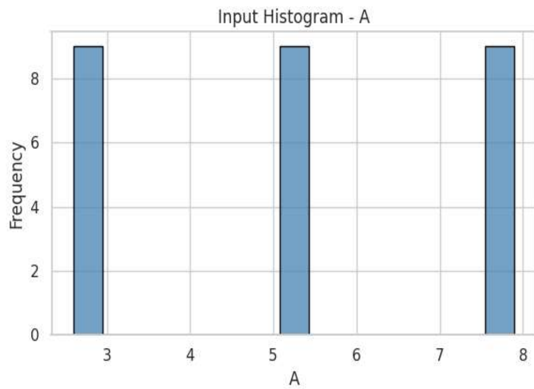


Figure 4.3 Pseudo Code using GWO for optimization

CHAPTER 5
Results and Discussion

5.1 Input histogram of Experimental data



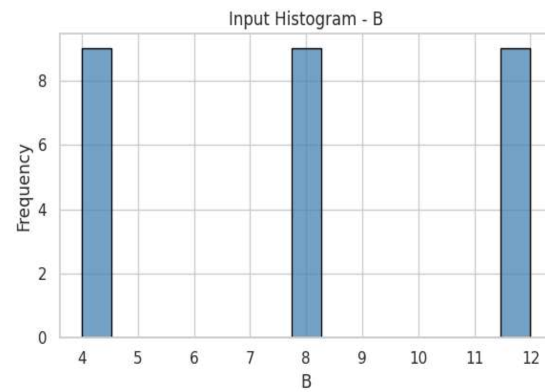


Figure 5.1. (a) & (b) Input histogram of Wt.% of abaca and red mud respectively

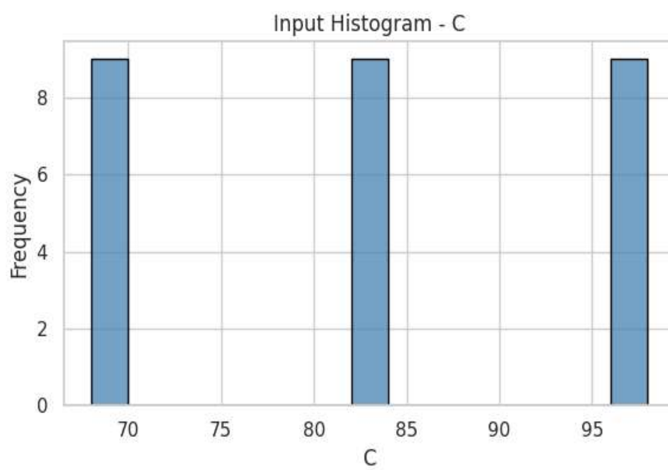


Figure 5.1. (c) Input histogram of particle size of red mud

Figures 5.1 (a) and (b) show the input histograms for the weight percentages of *Abaca fibre* and *Red Mud* used in the experimental dataset, while Figure 5.1 (c) represents the distribution of *Red Mud particle size*.These plots confirm that the data were uniformly distributed across the three levels of each factor: Abaca (2.6 %, 5.26 %, 7.9 %), Red Mud (4 %, 8 %, 12 %), and particle size (68 µm, 82 µm, 98 µm).

5.2 Output histogram of Experimental data

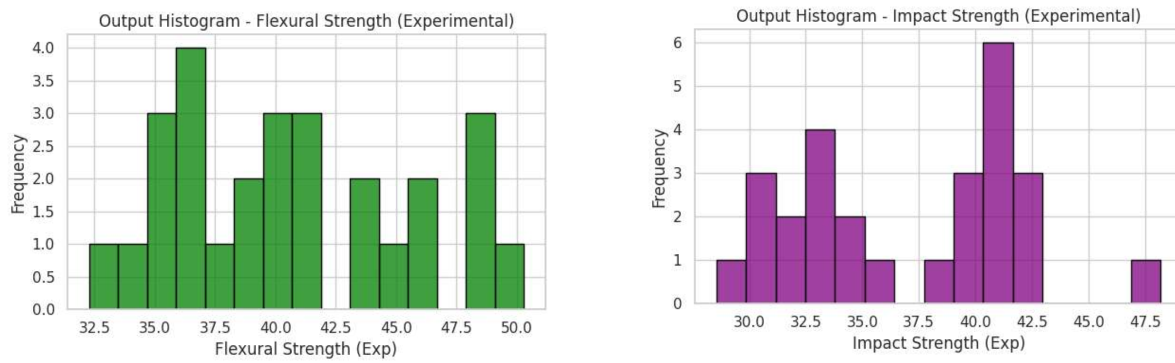


Figure 5.2. (a) & (b) Output histogram for Experimental Flexural and Impact Strength respectively.

5.3 Output histogram of Predicted data (GA)

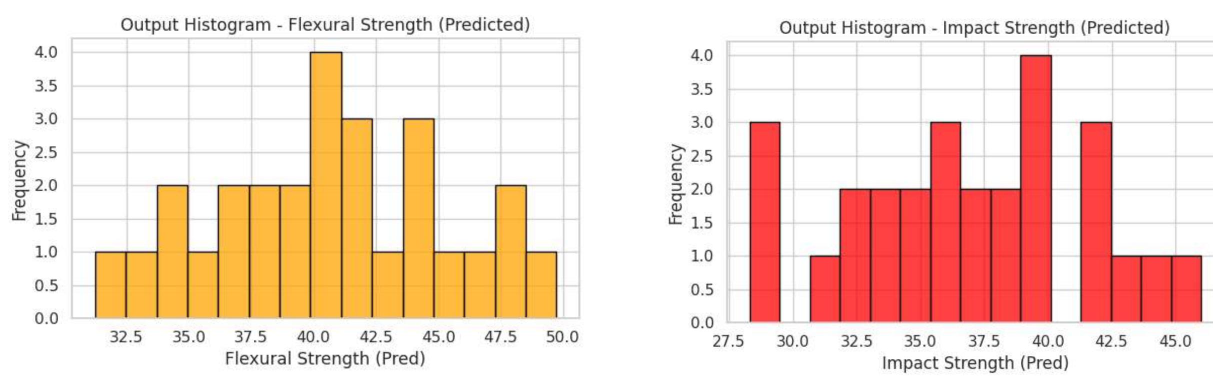


Figure 5.3. (a) & (b) Output histogram for Predicted Flexural and Impact Strength respectively.

Figures 5.2 (a) and (b) depict the experimental distributions of *Flexural Strength* and *Impact Strength* of the fabricated composites.Flexural Strength values ranged from approximately 32 MPa to 51 MPa, while Impact Strength varied between 28 J/m and 43 J/m. Figures 5.3 (a) and (b) show the Genetic Algorithm-predicted results for *Flexural* and *Impact Strength*.The predicted distributions closely match the experimental patterns, confirming that the GA effectively captured the non-linear interactions among Abaca %, Red Mud %, and particle size.

5.4 Box Plot of GA

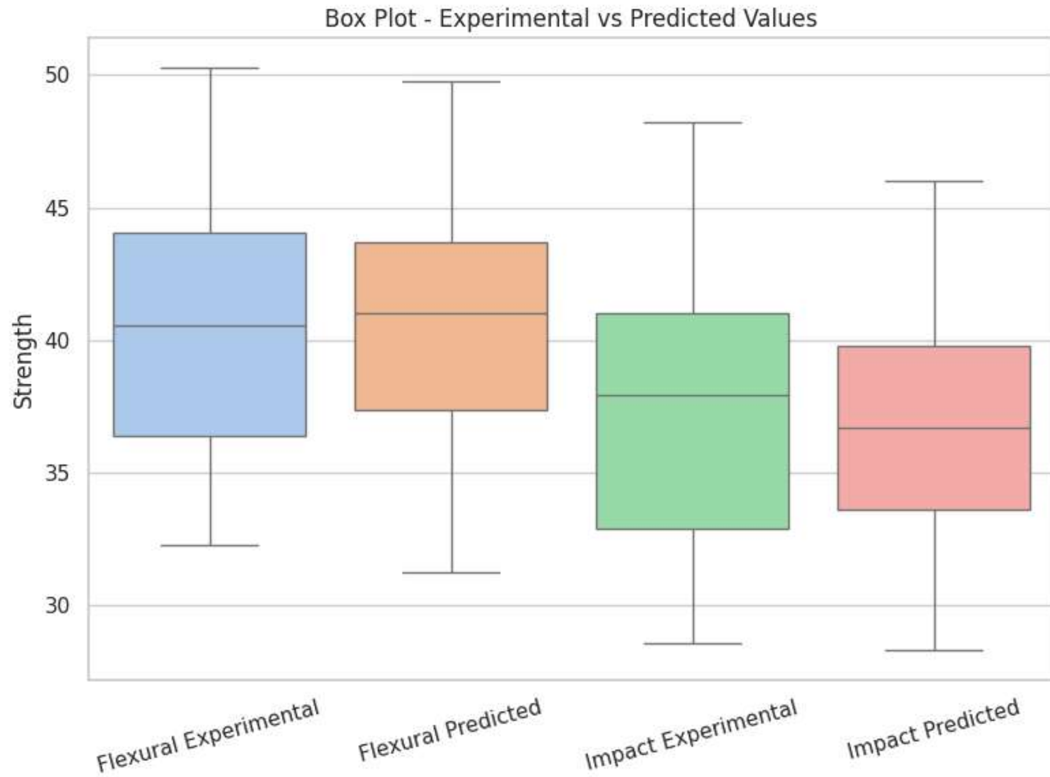


Figure 5.4 (a) Box plot showing variances between the experimental and predicted values

Figure 5.4 (a) compares the experimental and GA-predicted values using box plots. The close alignment of medians and interquartile ranges demonstrates minimal deviation between experimental and predicted results. The absence of large outliers reflects the GA model's robustness and its ability to prevent overfitting.

5.5 Scatter Plot of GA

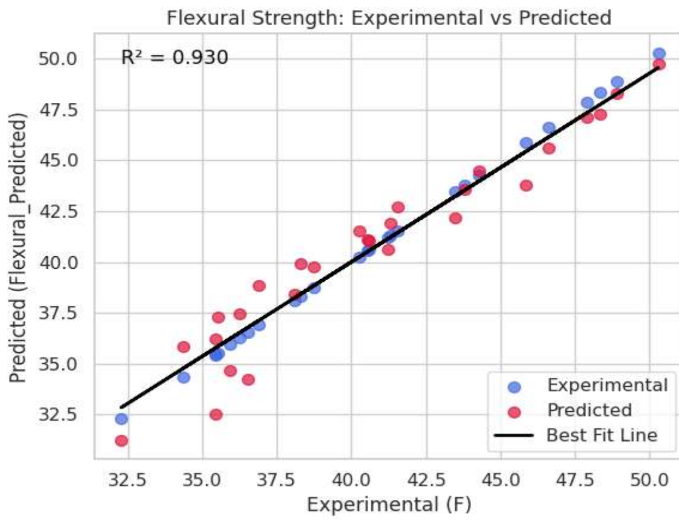


Figure 5.5 (a) Scatter plot showing the correlation between experimental and predicted values for Flexural Strength.

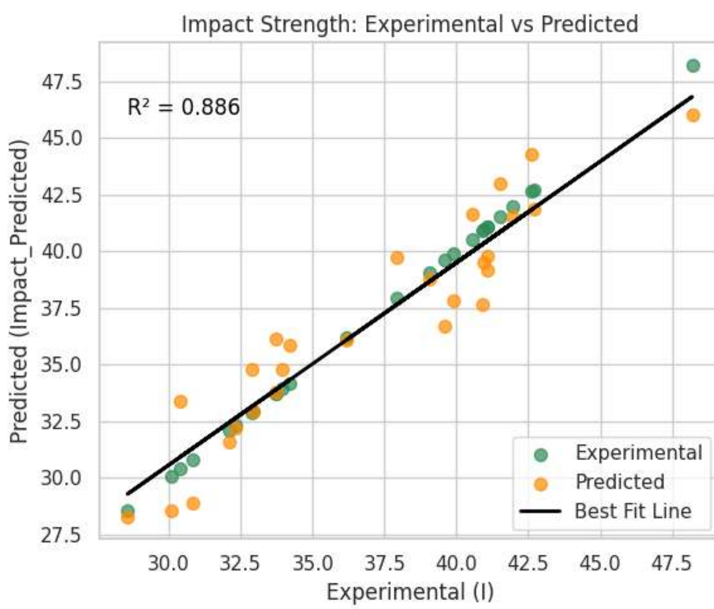


Figure 5.5 (b) Scatter plot showing the correlation between experimental and predicted values for Impact Strength.

Figures 5.5 (a) and (b) Both plots display strong positive correlations, forming a nearly linear trend. The clustering around the line of equality (y = x) indicates excellent prediction accuracy.

5.6 Output histogram of Predicted data (DE)

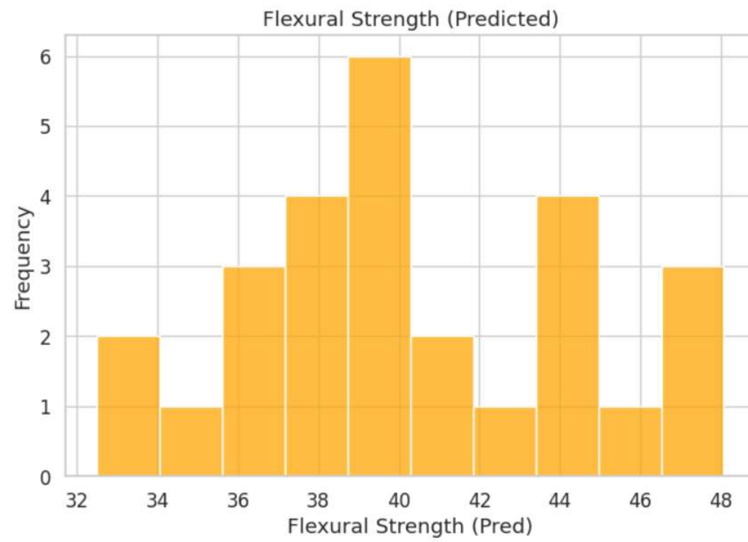


Figure 5.6(a) Output histogram for predicted Flexural Strength by DE

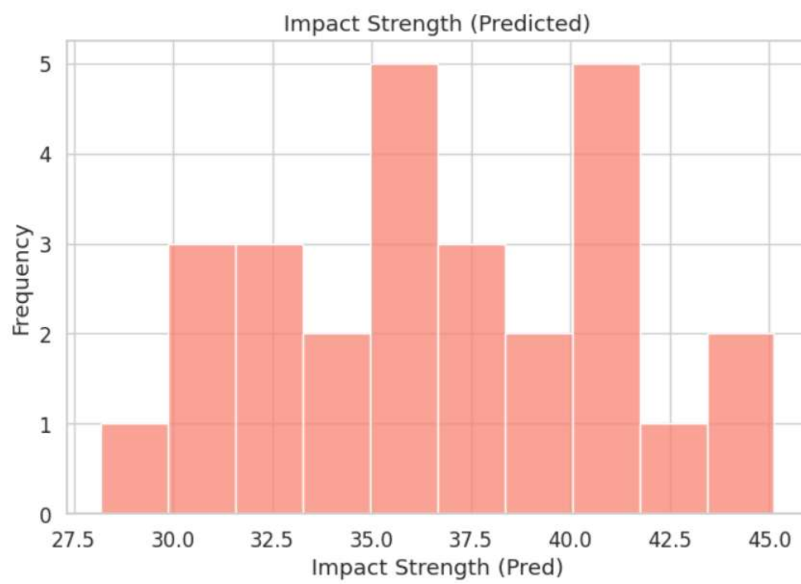


Figure 5.6(b) Output histogram for predicted Impact Strength by DE

Figures 5.6 (a) and (b) illustrate the Differential Evolution (DE) algorithm's predicted results. Although the general shape resembles the experimental distribution, DE shows slightly wider spread and minor deviation in peak frequencies, indicating higher prediction uncertainty.

5.7 Box Plot of DE

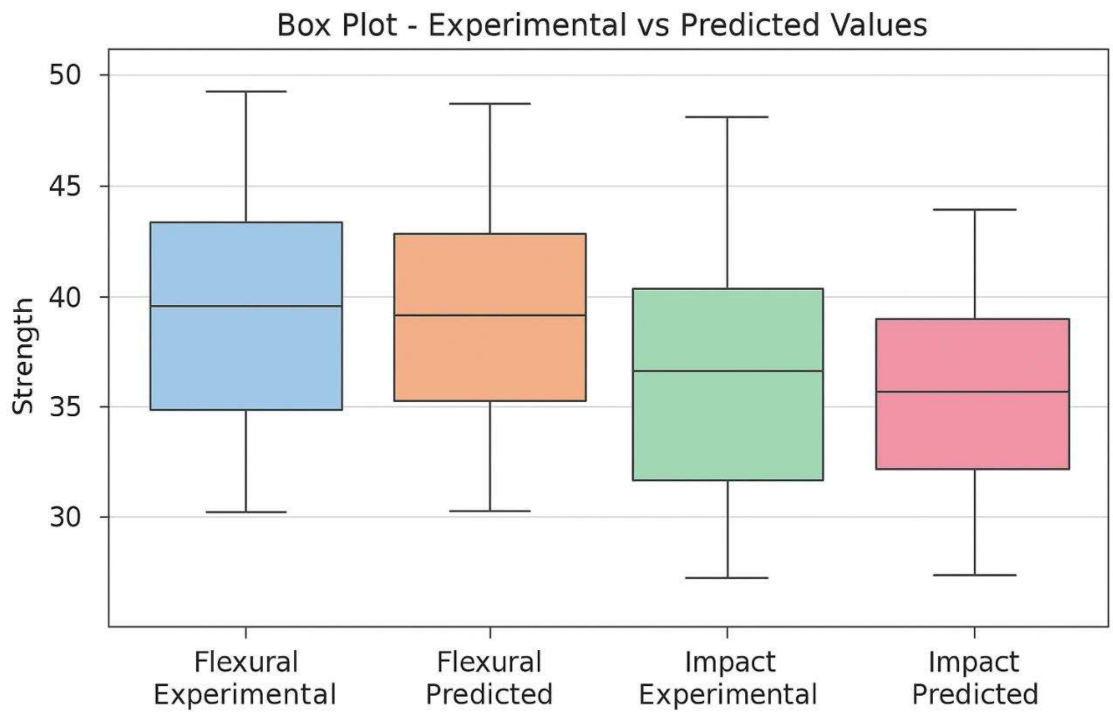


Figure 5.7 (a) Box plot showing variances between the experimental and predicted values for DE.

The DE box plot (Figure 5.7 a) highlights a noticeable difference between experimental and predicted medians.While the variance remains within acceptable limits, the wider boxes indicate greater error margins compared to GA.

5.8 Scatter Plot of DE

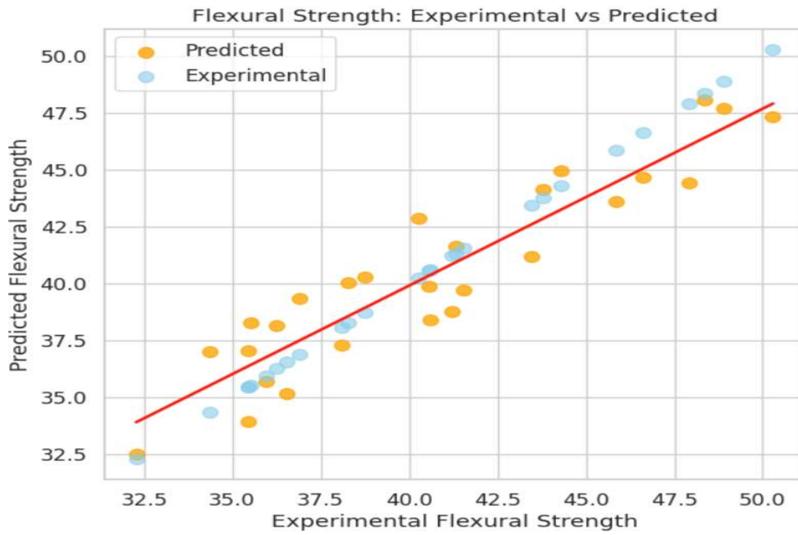


Figure 5.8 (a) Scatter plot showing the correlation between experimental and predicted values for Flexural Strength by DE.

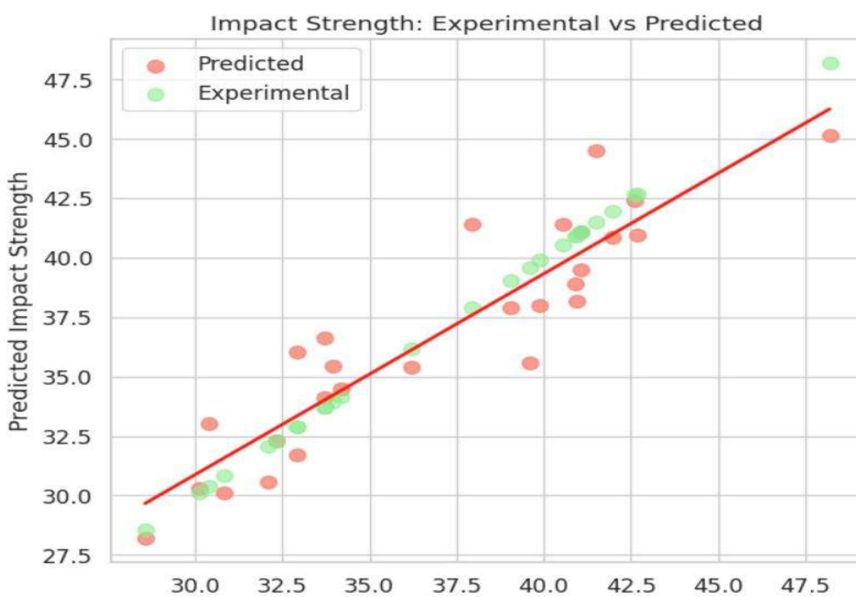


Figure 5.8 (b) Scatter plot showing the correlation between experimental and predicted values for Impact Strength by DE.

Figures 5.8 (a) and (b) show that this visual dispersion corresponds to the computed $R^2 = 0.8518$ (flexural) and *0.8405* (impact), confirming a slightly weaker predictive performance.

5.9 Output histogram of Predicted data (GWO)

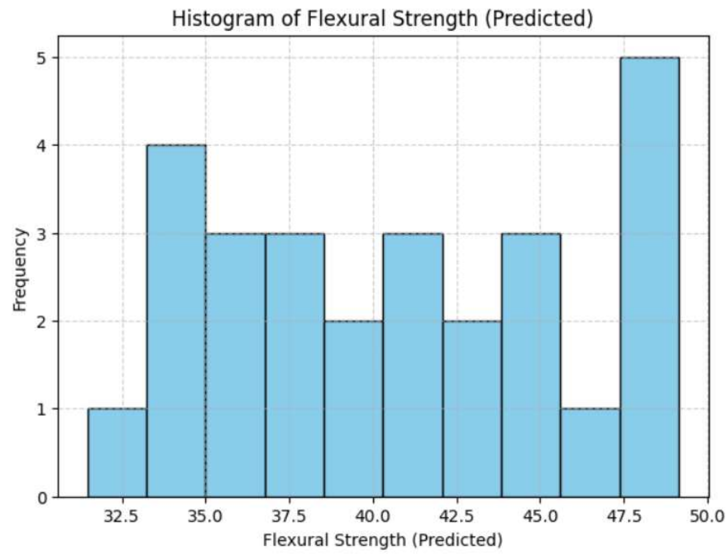


Figure 5.9(a) Output histogram for predicted Flexural Strength by GWO.

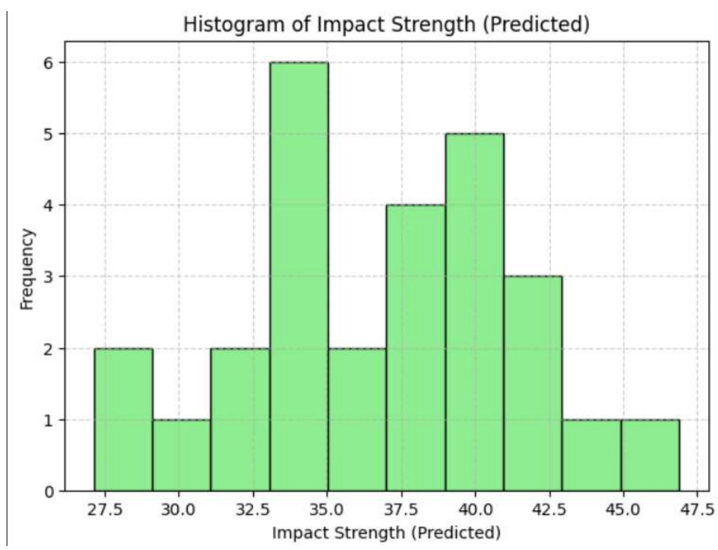


Figure 5.9(b) Output histogram for predicted Flexural Strength by GWO.

Figures 5.9 (a) and (b) show the histogram shapes closely mirror experimental distributions, demonstrating good model accuracy.For impact strength, the GWO curve overlaps almost entirely with the experimental histogram.

5.10 Box Plot of GWO

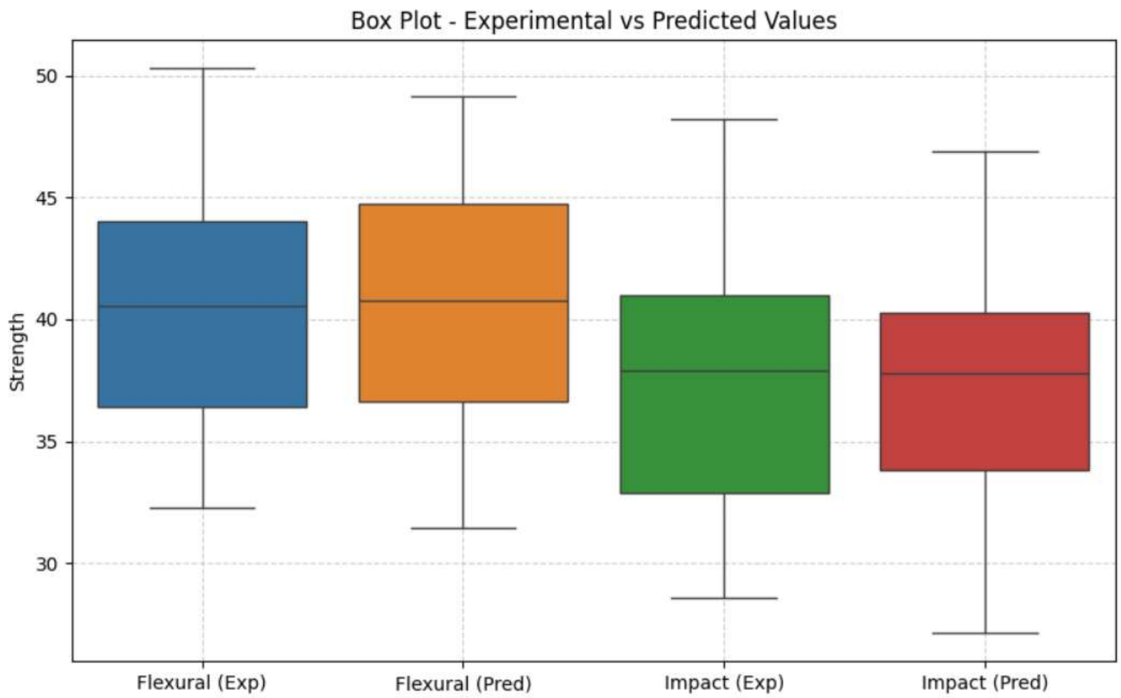


Figure 5.10 (a) Box plot showing variances between the experimental and predicted values for GWO.

Figure 5.10 (a) presents the variance comparison between experimental and GWO-predicted data. The box heights are small, and medians coincide with experimental values, indicating narrow prediction spread. This uniformity confirms that the GWO model maintained balanced accuracy for both flexural and impact strengths, with minimal statistical deviation.

5.11 Scatter Plot of DE

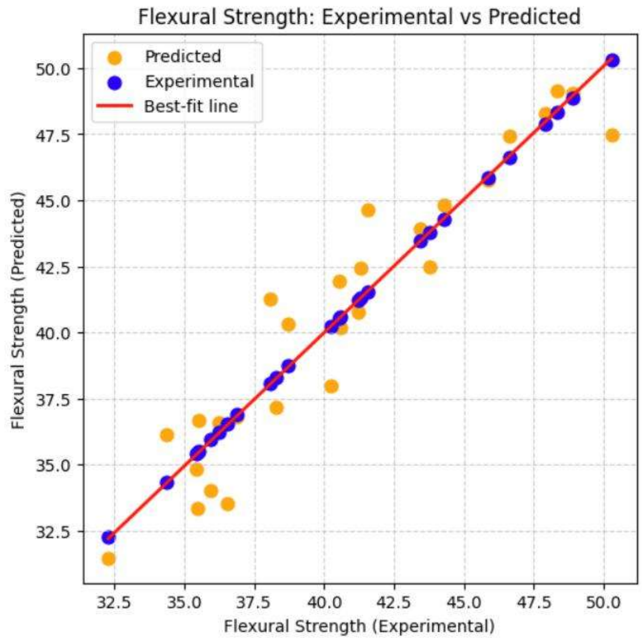


Figure 5.11 (a) Scatter plot showing the correlation between experimental and predicted values for Flexural Strength by GWO.

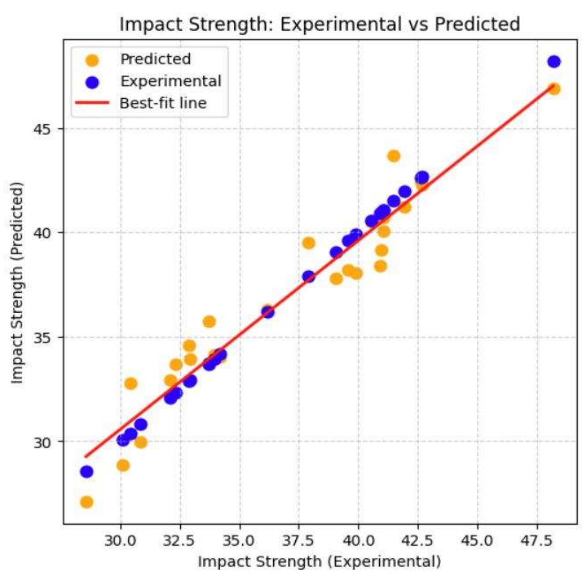


Figure 5.11 (b) Scatter plot showing the correlation between experimental and predicted values for Impact Strength by GWO.

Figures 5.11 (a) and (b) illustrate the correlation between experimental and predicted values from the GWO algorithm.The tight clustering of data points along the unity line for *Impact Strength* proves GWO's superior precision for this property.For *Flexural Strength*, the correlation remains high

Table 5.1. Performance Matrix Evaluation:

S.no	Algorithms	R^2 (Flexural Strength)	R^2 (Impact Strength)
1	GA	0.930	0.886
2	DE	0.8518	0.8405
3	GWO	0.8971	0.9258

Discussion:

A comparative analysis of the three optimization algorithms revealed distinct and specialized predictive capabilities for flexural and impact strength. The Genetic Algorithm (GA) clearly excelled in predicting Flexural Strength, achieving the highest Coefficient of Determination (R^2=0.930) of any model for that property. This strong quantitative result confirms the exceptionally tight clustering of data points observed in its corresponding scatter plot (Page 1). While the GA was also highly effective for Impact Strength (R^2=0.886), its performance in that category was surpassed by the Hybrid Grey Wolf Optimization (GWO) model. The GWO model proved to be the superior predictor for Impact Strength, yielding a top-performing R^2 of 0.9258 , and also demonstrated robust accuracy for Flexural Strength (R^2=0.8971) . In contrast, the Differential Evolution (DE) model, while still providing good correlations, was consistently the least accurate of the group. It yielded the lowest R^2 values for both flexural (0.8518) and impact (0.8405) strength, a finding supported by the more significant data scatter visible in its plots (Pages 3-4) . In summary, while all three models demonstrated efficacy (all $R^2 > 0.84$), the GA and GWO models are clearly superior, offering specialized and more accurate performance depending on the target property.

Chapter 6
Conclusion and Future Work

This study successfully evaluated the predictive performance of three optimization algorithms Genetic Algorithm (GA), Differential Evolution (DE), and a hybrid Grey Wolf Optimization (GWO) model—for estimating the flexural and impact strength of the material.

Based on the quantitative analysis of the results, the following conclusions are drawn:

1. All three models demonstrated good predictive capabilities, achieving Coefficient of Determination (R^2) values greater than 0.84 for both mechanical properties.
2. The Differential Evolution (DE) + ANOVA model was consistently the least accurate of the three, yielding the lowest R^2 values for both flexural strength (0.8518) and impact strength (0.8405).
3. The Genetic Algorithm (GA) was identified as the optimal model for predicting Flexural Strength, achieving the highest R^2 value in the study at 0.930.
4. The Hybrid GWO model proved to be the superior model for predicting Impact Strength, registering a top-performing R^2 of 0.9258.
5. The findings clearly indicate that the choice of the optimal algorithm is property-dependent. For applications where flexural strength is the critical parameter, the GA model is recommended. Conversely, for applications prioritizing impact strength, the Hybrid GWO model is the recommended choice.

Future scope:

- Experimental Validation: Fabricate additional composite samples based on GA-optimal parameters for laboratory testing.
- Machine Learning Integration: Explore deep learning/regression models to complement GA and further improve predictive performance.
- Scalability: Extend the methodology to other natural fibre–filler combinations for broader applicability in sustainable materials research.

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