



Preparation, Characterization and Optimization of a Novel Natural Fibre Based Composites using GRA and Topsis Technique.

¹Dr.M.Srinivasa Rao, ²S.Vamsi, ³T.Dineshkumar, ⁴R.Someswara Rao, ⁵V.Viswanath Ganesh, ⁶P.Mohan Thulasiram

^{1,2,3,4,5,6}Department of Mechanical Engineering, GMR Institute of Technology, Rajam- 532127.

DOI: <https://doi.org/10.55248/genpi.2023.4.34024>

ABSTRACT:

Over the years, the natural fiber reinforced Composite materials are gaining a supreme demand in the fabrication industry of various materials owing to their low cost, biodegradable and good mechanical, electrical and thermal properties. The goal of this study was to enhance the Mechanical performance of composites made from Pineapple leaf fiber, Coconut shell powder, and Tectonasgrandis leaf powder as a reinforcement and Epoxy resin as their matrix using the Hand layup technique. The composites were reinforced with 0-30 wt% fiber and 0-30 wt% coconut shell and Tectonasgrandis and their combinations respectively. Mechanical tests like Tensile, Compression, Impact and Hardness tests are conducted on the specimens. The composites produced good results like 14.74 MPa Tensile, 29.51 Compression MPa, 0.046 J/mm² Impact Strength for Hybrid Composite material. The same results were optimized using various analyzing Techniques. Through the use of Taguchi-based grey relational analysis (GRA) and technique for order preference by similarity to ideal solution (TOPSIS) methods, The best conditions for achieving the best mechanical properties in the developed composites were identified. The results showed that the hybrid reinforced composite material outperformed other combinations in terms of mechanical properties.

Keywords: Natural Composites, Mechanical properties, Grey-relational analysis (GRA), Technique for order preference by similarity to ideal solution (TOPSIS), Pineapple leaf fiber (PLF), Coconut shell Activated Carbon (CS), Tectonasgrandis leaves (TL).

INTRODUCTION:

The global community is becoming increasingly aware of the need for sustainable practices to reduce the use of non-biodegradable materials such as plastics. In the polymer industry, natural fibers are emerging as a substitute for synthetic fibers. Synthetic fibers pose environmental concerns and health hazards due to their non-biodegradable nature. Because of their abundance, natural fibres such as pineapple, sisal, kenaf, bagasse, ramie, banana, and others are preferred., properties, and geographical impact. The overall properties of natural fiber reinforcement depend on the presence of cellulose, hemicellulose and lignin. Composite materials are known for their durability, stability, erosion resistance, and lightweight, making them increasingly popular in material science and design. A composite material is a combination of at least two constituent materials, each possessing unique physical or chemical properties, that results in the formation of a material with remarkable properties that differ significantly from those of the constituent parts. This advancement has led to composite materials possessing superior properties compared to individual materials. Composite materials, like natural composites such as wood, are comprised of fibrous chains of cellulose particles in a matrix. The concept of composite materials involves combining one or multiple fibers with a suitable matrix to produce composite laminates that are tailored to specific applications. These composites find use in various applications, such as automobile, aerospace, and household polymeric industries. While fiber composites offer many benefits, In addition, composite materials may also have some disadvantages such as low interfacial adhesion between the fibers and matrix, resulting in poor fiber/matrix adhesion, and high water absorption, which can lead to a reduction in mechanical properties over time. In order to solve this problem, the addition of fiber with other filler elements comprised of single or multi-elements showed a great impact on the mechanical thermal and electrical properties of the composite material. There comes the notion of Hybrid Composite materials. In addition, hybridization can also address the issue of low impact strength. By incorporating multiple natural fiber reinforcements, hybridization has been identified as a promising technique in composite fabrication. The combination of multiple fibers with a single fiber in a polymer matrix has resulted in the development of hybrid composites. This technique compensates for the weaknesses of one fiber with the strengths of another fiber, resulting in improved overall properties. Natural hybrid composites refer to composite materials that are created using a combination of multiple natural fibers, rather than a single type of fiber. These fibers can be derived from different plant sources or from a combination of plant and animal sources. The resulting composite material has improved mechanical properties compared to single fiber composites, as it can leverage the strengths of each individual fiber. Examples of natural hybrid composites include bamboo-glass, bamboo-jute, and bamboo-sisal composites. These composites have shown improved mechanical properties such as increased tensile strength, flexural strength, and impact resistance compared to single fiber composites. Natural hybrid composites have gained attention in recent years due to their eco-friendly and sustainable nature. The use of natural fibers as reinforcement materials in composites supports the development of green

and environmentally responsible technologies. Additionally, natural fibers are renewable, biodegradable, and have a low environmental impact compared to synthetic fibers.

Natural fillers are a type of reinforcing material that is added to composite materials to enhance their mechanical properties. These fillers are derived from natural sources such as plants, animals, and minerals. They are becoming increasingly popular as an alternative to synthetic fillers due to their biodegradability, low cost, and renewability. Some commonly used natural fillers in composites include wood flour, cellulose, sisal fibers, coconut fibers, and hemp fibers. These fillers are often added to thermoplastics, thermosets, and biopolymers to enhance their strength, stiffness, and impact resistance. Natural fillers can also improve the thermal and electrical properties of the composites. The use of natural fillers in composites has several benefits. They are lightweight, have a low environmental impact, and are renewable. Natural fillers also improve the biodegradability of the composite, making them more environmentally friendly. However, the use of natural fillers in composites may result in some challenges such as processing difficulties and inconsistent properties due to variations in the filler quality. Hybrid green composites have been found to possess a similar toughness to that of high-tensile steel, despite being lower in toughness than carbon fiber. This makes them a promising alternative to traditional materials such as steel and hard plastics in the manufacturing of automobile parts like bumpers, window cladding, bonnets, dashboards, armrests, and more. The use of such composites would not only reduce the weight of automobile components but also reduce the amount of torque required to pull the vehicle.

The hydrophilic nature of the fibers was observed to reduce after treatment, leading to improved bonding. This, in turn, improved the compatibility of the fibers with the matrix and consequently led to improved mechanical properties. Optimization is a crucial aspect in determining the optimal experimental conditions. Response surface optimization methods and Taguchi-based multi-response optimization have been employed in various research works. The mechanical properties of Coconut shell, Tectonagrandis, and pineapple fiber-based epoxy composites were optimized using these techniques to obtain the best possible conditions. In the current scenario, it is imperative to determine the best conditions for improving mechanical properties to reduce raw material waste and increase process efficiency. In this study, natural fibers were used to create composite laminates using the hand layup technique and epoxy as the matrix material. Multi-response optimization with GRA and TOPSIS was employed to determine the best conditions for enhancing mechanical properties.

MATERIALS AND METHODS:

Materials

For this experiment, reinforcement materials were selected from Coconut shell, Tectonagrandis, and pineapple fiber, which are readily available in southern India. The Pineapple fiber is collected from Chennai. The preparation of Activated Carbon from Coconut Shells starts by collecting Shells and cleaning them with water to prevent from dirt. After that it is burnt in a Muffle Furnace at 600-800°C for 2-3 hours and it is cooled at room temperature. After that it is crushed using a hammer and again kept in a furnace for about 800-1000°C which is called activation process. After that it is cooled and crushed with a grinder. Rinsing with water helps to remove impurities from the Activated Carbon Powder. Collecting the tectonagrandis leaves and burning them in the open air yields Tectonagrandis leaf powder. The matrix material used was a combination of standard-grade LY556 epoxy resin and HY951 hardener in a 10:1 ratio which is purchased from VH Enterprisers, Chennai.

Sieve Analysis

A gradation test, also known as sieve analysis, is a technique widely used in chemical and civil engineering to determine the particle size distribution of granular materials. It involves measuring the percentage of material retained by each sieve as a fraction of the total mass, and the particle size distribution is known to significantly affect the material's performance in various applications. This test can be applied to different types of granular materials such as sand, crushed rock, clay, soil, powders, grains, seeds, among others, with varying levels of accuracy. Our analysis employed a mesh size of 85 (0.1776mm) for Tectonagrandis leaf powder and 120 (0.124mm) for Activated Coconut Shell powder.

Natural fiber composite fabrication

The development of epoxy composites using Coconut shell, Tectonagrandis, and pineapple fiber at various weight percentages ranging from 0 to 10 was achieved using the hand layup technique. The fiber material is combed and cut to a size of 5 to 7 mm and laid along the mold. To produce better wetting of the fiber and fewer voids in the part a Silicon Spray layup is used. To fabricate the composites, a mild steel rectangular mold measuring 100 x 100 x 10 mm was used. The resin mixture was evenly spread into the mold using a roller until it reached the desired thickness. The top plate was then placed on the mold with a compressive force and left at room temperature for 24 hours. After removal from the mold, the specimens were trimmed to a uniform size.

Characterization of the natural composites

The mechanical properties of the composites produced were evaluated using various tests, including tensile, hardness test and impact tests, following the guidelines outlined in ASTM D638 and ASTM D256. To assess the tensile properties, a dog bone-shaped sample measuring 260 mm by 50 mm and with a mid-span width of 30 mm was cut from the composites and fixed between the grippers of a universal testing machine (UTM) The sample was subjected to a constant load until failure occurred at a crosshead speed of 5 mm/min. The resistance of a material to indentation or scratching by a harder object was evaluated using the hardness test. A sample measuring 50 mm by 10 mm was employed for this test. The energy absorbed during impact was measured using an Izod impact test machine and a 75 mm by 10 mm sample size. Similarly, using a sample size of 55 mm by 10 mm, the Charpy impact test machine was used to measure the energy absorbed during impact.

Optimization of composites by using Taguchi Method

Taguchi optimization is a methodology employed to analyze diverse data by taking into account numerous factors and levels. Its purpose is to investigate the impact of input variables in different applications. This study evaluated the tensile strength, impact strength (IS), and compression test for composites composed of pineapple leaf fiber, activated coconut shell (AC), and Tectonasgrandis leaves (AC), using various combinations. The input factors were both the weight of the reinforcing fiber and AC. The Taguchi method is a statistical approach to quality control that involves optimizing the performance of a system or product by minimizing the impact of noise factors.

The Taguchi method is a statistical technique commonly used to optimize system performance by minimizing the impact of noise factors. In this study, we applied the Taguchi method to optimize the mechanical properties of polymer-based composites made of pineapple leaf fiber, coconut shell (AC), and Tectonasgrandis leaves (AC). We measured the quality characteristics of all configurations and chose the signal-to-noise (SN) ratio, which indicates that a higher value is better, to evaluate the mechanical properties using the below equation. We performed the optimization using Minitab 21.1 statistical software and examined three factors, including the weight percentage of pineapple leaf fiber (0-30 wt%), coconut shell (AC) (0-30 wt%), and teak leaves (AC) (0-30 wt%). The bonding strength between the fiber and matrix phases is a key factor that influences the mechanical strength of polymer-based composites. To determine the optimal combination of input factors, we used the L9 orthogonal array, which is a powerful tool for experimental design that minimizes the impact of confounding factors.

Here n is the number of results and “ Y_i ” is results of combinations.

Table 1: Taguchi Optimization of Composites for L9 orthogonal array.

Sl.no	wt% of PLF	wt% of CS	wt% of TL	TS Mpa	CS Mpa	IS J/mm ²	SN ratio of TS	SN ratio of CS	SN ratio of IS
1.	0	30	0	4.59	13.58	0.028	13.2363	22.6580	-31.0568
2.	0	0	30	5.29	13.32	0.029	14.4691	22.4901	-30.7520
3.	0	15	15	7.18	20.36	0.038	17.1225	26.1756	-28.4043
4.	15	30	30	14.74	29.51	0.046	23.3699	29.3994	-26.7448
5.	15	0	15	6.51	23.17	0.041	16.2716	27.2985	-27.7443
6.	15	15	0	5.69	25.59	0.046	15.1022	28.1614	-26.7448
7.	30	30	15	12.22	24.32	0.042	21.7414	27.7193	-27.5350
8.	30	0	0	7.78	12.89	0.032	17.8196	22.2051	-29.8970
9.	30	15	30	13.62	25.62	0.041	22.6835	28.1716	-27.7443

Grey Relational Analysis for Multi-Response Optimization (GRA)

The Taguchi approach is a statistical method used to optimize the performance of a product or process by systematically varying multiple variables. However, when there are multiple responses involved, it can be challenging to determine the optimal combination of variables that leads to the best results. To overcome this challenge, the Grey Relational Analysis (GRA) method is an effective multi-response optimization technique that combines all responses into a single result. By using GRA, the best fabrication conditions can be determined for composites, resulting in enhanced mechanical properties. The first step in the optimization process involved converting the response into a normalized form. Similar to the Taguchi approach, the "larger the better" method was applied, where the goal is to maximize the response. By using the below equation.

$$y_i^* k = \frac{x_i^0 k - \min x_i^0 k}{\max x_i^0 k - \min x_i^0 k}$$

In the given equation, "i" represents the experiment number and "k" represents the quality function being evaluated. Then, $x_i^0 k$ is response for each experiment, followed by “ $\min x_i^0 k$ ”, “ $\max x_i^0 k$ ” is lowest and highest responses from “ $x_i^0 k$ ” results. The normalized results were transformed into grey relational coefficients (GRC) using the following equation in the subsequent step.

$$\xi_i^* k = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{0i} k + \zeta \Delta_{\max}}$$

In this Δ_{oi} k is the offset values with $y_i^*(k)$ as the reference and $y_i^-(k)$ as the comparability series. ζ is called as characteristic coefficient with 0.5 reading. The smallest and largest values of Δ_{oi} k are termed as Δ_{min} and Δ_{max} .

In the final stage, the individual mechanical results GRC values were combined to generate a single response variable known as the Grey relational grade (GRG) using equation. The maximum value of GRG represents the most improved mechanical property.

$$y_i = \frac{1}{n} \sum_{k=1}^n \xi_i k$$

In the equation, "y_i" represents a quality characteristic that ranges from 0 to 1, and "n" represents the total number of experiments. The variables "i" and "k" are used to represent the experiment number and the quality function, respectively.

Table 2: Grey-relational analysis of composites.

Sl.no	Normalized TS	Normalized CS	Normalized IS	GRC TS	GRC CS	GRC IS	GRG	Rank
1.	0.0000	0.0415	0.0000	0.3333	0.3428	0.3333	0.3365	9
2.	0.0690	0.0259	0.0556	0.3494	0.3392	0.3462	0.3449	8
3.	0.2552	0.4495	0.5556	0.4017	0.4759	0.5294	0.4690	6
4.	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
5.	0.1892	0.6185	0.7222	0.3814	0.5672	0.6429	0.5305	5
6.	0.1084	0.7641	1.0000	0.3593	0.6795	1.0000	0.6796	3
7.	0.7517	0.6877	0.7778	0.6682	0.6156	0.6923	0.6587	4
8.	0.3143	0.0000	0.2222	0.4217	0.3333	0.3913	0.3821	7
9.	0.8897	0.7659	0.7222	0.8192	0.6811	0.6429	0.7144	2

Multi-response optimization using Technique for Order Preference by Similarity to Ideal Solution method (TOPSIS)

The TOPSIS methodology is a useful tool for combining multiple responses into a single response optimization to improve the tensile, impact and hardness properties. This complements the GRA approach and provides a comprehensive solution for optimizing material properties. Implementing the TOPSIS technique involves several steps. Using GRA and TOPSIS together can validate and confirm the optimized results.

The first step is to organize the response data into a matrix format, as illustrated below. In this matrix, q_{ij} denotes the response value of the material properties at their respective trial.

$$D_m = \begin{bmatrix} q_{11} & q_{12} & q_{13} & \dots & \dots & q_{1n} \\ q_{21} & q_{22} & q_{23} & \dots & \dots & q_{2n} \\ q_{31} & q_{32} & q_{33} & \dots & \dots & q_{3n} \\ \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\ q_{m1} & q_{m2} & q_{m3} & \dots & \dots & q_{m1} \end{bmatrix}$$

The next step involves normalization, which is accomplished using the following equation.

$$r_{ij} = \frac{q_{ij}}{\sqrt{\sum_{i=1}^m q_{ij}^2}}$$

The third step in the decision-making process involves calculating the weighted normalized matrix by multiplying the assigned weightage values for each property with their corresponding normalized values. This step is crucial as it considers the relative importance of each property in the overall decision and provides a more accurate representation of the criteria. The formula used for this step is presented below.

$$V = w_{ij} \times r_{ij}$$

Step four involves determining the Ideal Best (S+) and Ideal Worst (S-) values using the below formulas are used respectively. For beneficial criteria such as improving mechanical properties, the Ideal Best value is the maximum value of the weighted normalized values, while the Ideal Worst value is the minimum value of the weighted normalized values. These values are used in the subsequent step to calculate the distance of each alternative from the Ideal Best and Ideal Worst values.

$$S^+ = \sqrt{\sum_{j=1}^n (V_{ij} - V_j^+)^2}, i = 1, 2, \dots, i$$

$$S^- = \sqrt{\sum_{j=1}^n (V_{ij} - V_j^-)^2}, i = 1, 2, \dots, i$$

The next step in the decision-making process involves calculating the performance or closeness coefficient (CC) using the Euclidean distance between the Ideal Best (S+) and Ideal Worst (S-) values, as given by the formula provided below. This step is important in evaluating the proximity of each alternative to the Ideal Best and Ideal Worst values, and provides a measure of how well each alternative meets the decision criteria.

$$y_i = \frac{1}{n} \sum_{k=1}^n \xi_{ik}$$

The final stage of TOPSIS involves assigning ranks to each alternative based on their calculated closeness coefficient. Alternatives with higher closeness coefficient values are assigned higher ranks, ranging from 1 to 9. This ranking process provides a clear and concise way of comparing and evaluating the alternatives based on their relative performance against the decision criteria.

Table 3: TOPSIS of composites.

Sl.no	N TS	N CS	N IS	WN TS	WN CS	WN IS	S+	S-	CC	Rank
1.	0.1635	0.2082	0.2414	0.0505	0.0228	0.1404	0.1461	0.0000	0.0000	9
2.	0.1884	0.2042	0.2500	0.0582	0.0224	0.1454	0.1372	0.0001	0.0006	8
3.	0.2558	0.3122	0.3276	0.0790	0.0342	0.1906	0.0937	0.0035	0.0359	6
4.	0.5251	0.4525	0.3966	0.1623	0.0495	0.2307	0.0000	0.0214	1.0000	1
5.	0.2319	0.3553	0.3535	0.0717	0.0389	0.2056	0.0946	0.0050	0.0501	5
6.	0.2027	0.3924	0.3966	0.0626	0.0430	0.2307	0.0998	0.0087	0.0806	4
7.	0.4353	0.3729	0.3621	0.1345	0.0408	0.2106	0.0353	0.0124	0.2591	3
8.	0.2772	0.1977	0.2759	0.0856	0.0216	0.1605	0.1076	0.0016	0.0150	7
9.	0.4852	0.3929	0.3535	0.1499	0.0430	0.2056	0.0287	0.0146	0.3370	2

RESULTS AND DISCUSSIONS

Taguchi method for optimization

In this study, the optimization of pineapple fiber, coconut shell and tectonagrandis at various weight percentages was carried out using the Taguchi method. The factors of pineapple leaf, coconut shell and tectonagrandis varied from 0 to 30 wt%. Table 1 displays the SN ratio for the analysis of mechanical properties, including tensile, compression, and impact. The L9 orthogonal array was utilized to determine the properties, and the highest SN ratio provided better results. The combination of pineapple fibers at 15 wt%, coconut shell at 30 wt% and tectonagrandis at 30 wt% shows the highest TS of 95.50N/mm² in the fourth trial. Additionally, the highest impact and compression test values of 66.88N-mm and 61.81N/mm² respectively, were obtained at the ninth and seventh trials.

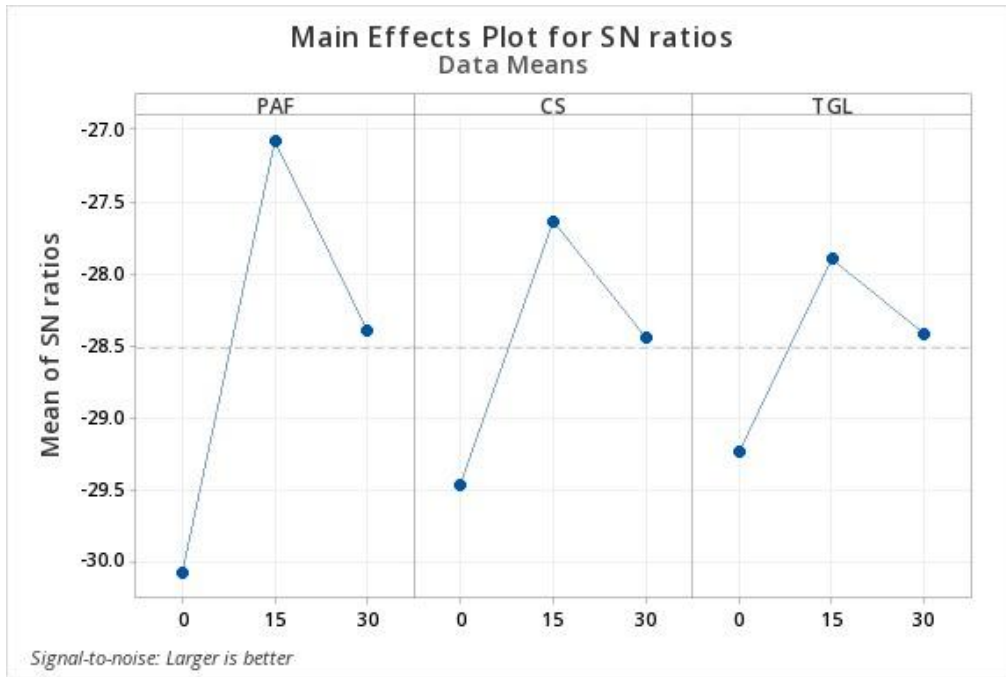


Fig 1: Signal to noise ratio of Impact Strength(IS)

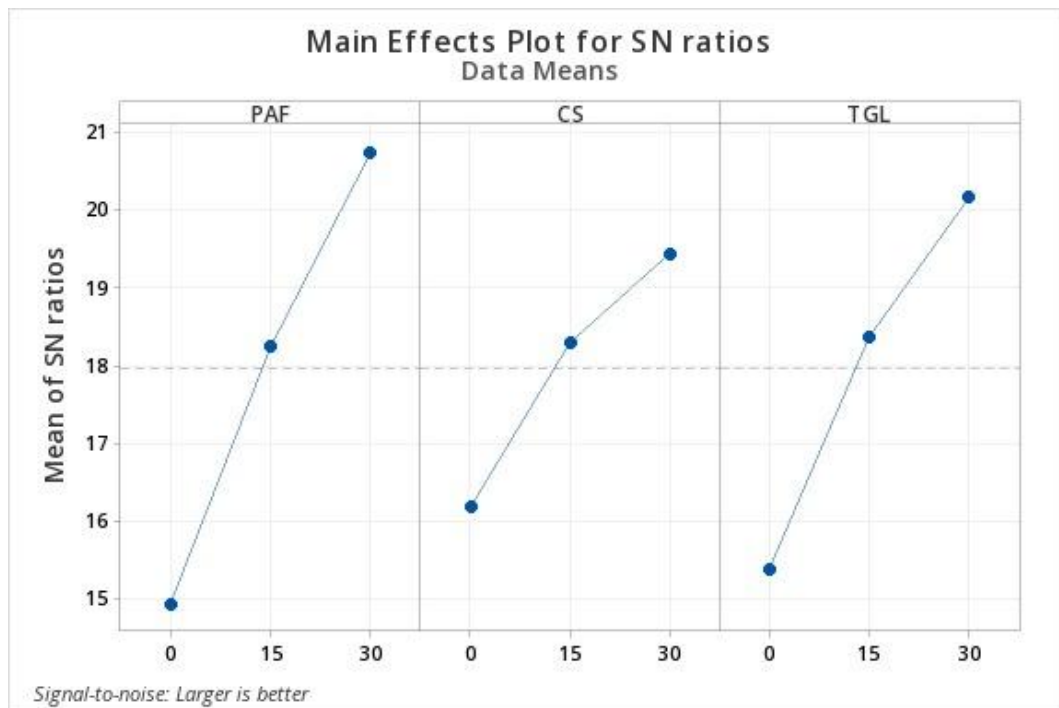


Fig 2: Signal to noise ratio of Tensile Strength(TS)

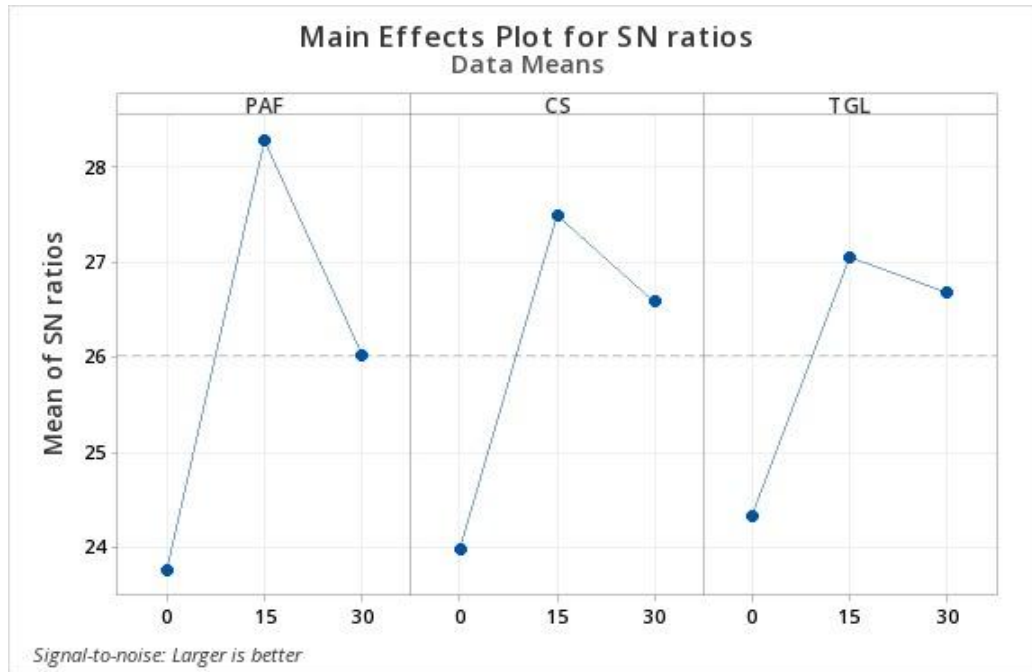


Fig 3: Signal to noise ratio of Compression Strength(CS)

Tensile Strength (TS) of the composites

The ultimate TS of the composites improved with the addition of pineapple fiber and tectonagrandis, demonstrating an enhancement in tensile properties. The optimized ultimate TS results were obtained with the combination of pineapple fibers at 15 wt%, coconut shell at 30 wt% and tectonagrandis at 30 wt%. The addition of fibers contributed to the enhancement of ultimate TS in the developed composites. Incorporating pineapple fiber within a certain range has been found to improve the tensile properties of polymer-based composites.

Compression Strength (IS) of the composites

The compression strength of the composites improved with the addition of pineapple fiber and coconut shell, demonstrating an enhancement in compression strength. The optimized CS results were obtained with the combination of pineapple fibers at 15 wt%, coconut shell at 30 wt% and tectonagrandis at 30 wt%. The addition of fibers contributed to the enhancement of CS in the developed composites.

Impact Strength (IS) of the composites

The IS was utilized to evaluate the impact properties of the composites. The incorporation of reinforcement fibers in 30wt% resulted in an increase in the IS of the epoxy- based composites. The proper adhesion between the fibers and matrix contributed to the enhancement of impact properties. The highest IS value was observed for pineapple fiber at 30wt%, coconut shell at 15wt%, and tectonagrandis at 30wt%. However, exceeding a certain limit of coconut shell led to a decrease in the IS value. It can be concluded from the findings that the substitution of up to 15 wt% fibers resulted in an increase in the IS of the polymer-based composites.

Multi-response optimization was applied using GRA

The mechanical strength of natural fiber hybrid composites was optimized using Grey relational analysis, which converted three response analyses into a single response data-set, resulting in increased clarity. The research findings, which are outlined in Table 3, indicate that the best trial combination was the fourth one, featuring 30 wt% coconut shell(AC) and 15 wt% pineapple leaf fiber and 30 wt% teak leaves(AC). By calculating delta values and ranking the each factor, with natural pineapple leaf fiber taking the top positions (as demonstrated in Table 2), which highlights the importance of natural fibers in boosting mechanical strength.

Table 4:Response table for S/N ratio of GRA

Level	PLF	CS	TL
1	0.38347	0.736699658	0.585067129
2	0.41918	0.621000143	0.665061607
3	0.46606	0.552734781	0.686438759
Delta	0.0826	0.183964876	0.10137163
Rank	3	1	2

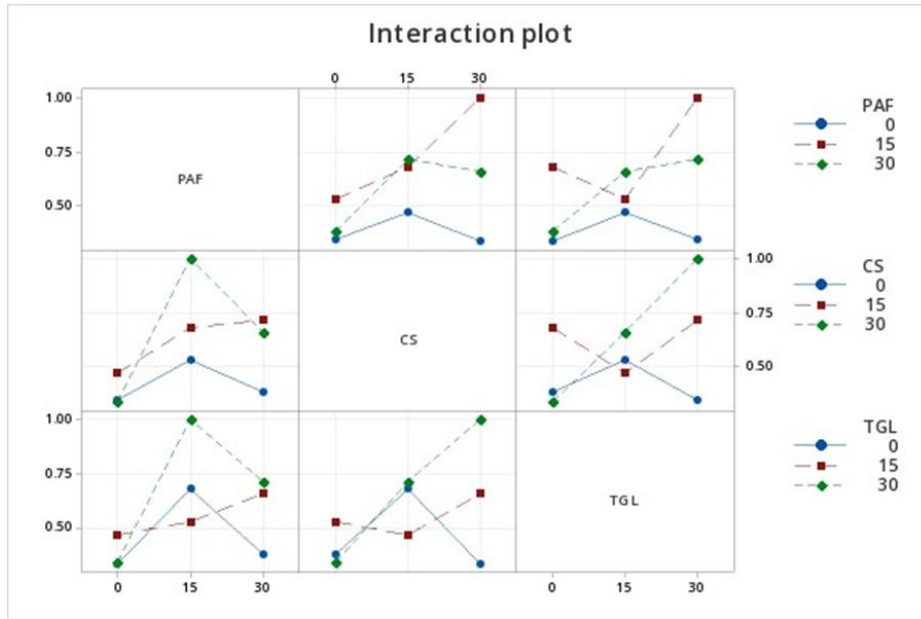


Fig 4: Minitab interaction plot for GRA results

Multi-response optimization was applied using TOPSIS method.

To validate the results obtained from grey relational analysis, TOPSIS was used in this study. Multi-response optimization through TOPSIS also showed similar findings, with the fourth trial combination of 15 wt% pineapple leaf fiber and 30 wt% coconut shell(AC), along with 30 wt% tectona leaves(AC), exhibiting the highest mechanical properties (as demonstrated in Table 5). The response table of TOPSIS, as shown in Table 6, also supports the notion that natural fibers enhance the mechanical properties of composites. Moreover, the weight percentages of pineapple leaf fiber and tectonagrandisleaves(AC) were found to have the most significant impact on improving the overall mechanical properties of the polymer-based composites. The coconut shell(AC), on the other hand, ranked third in TOPSIS optimization.

Table 4:Response table for S/N ratio of TOPSIS

Level	PLF	CS	TL
1	0.0122	0.0219	0.0319
2	0.3769	0.2107	0.1150
3	0.2037	0.4197	0.4459
Delta	0.1986	0.2174	0.1976
Rank	3	1	2

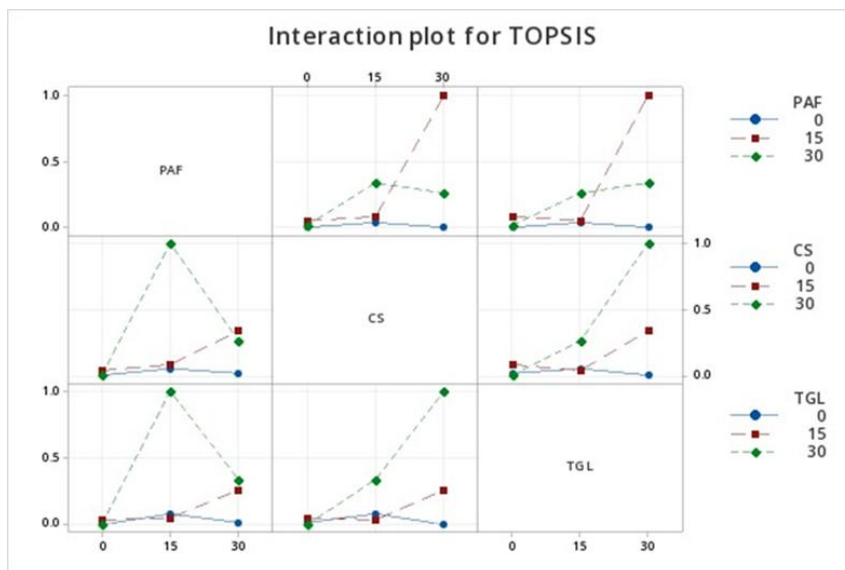


Fig 5: Interaction plot for TOPSIS results using Minitab

Prediction of Grey Relational Grade using ANN:

The ANN is used to predict GRG, ANN consists of three layers, the input layer consists of three nodes, one for each feature in the dataset. The hidden layer consists of five nodes, which apply a non-linear transformation to the input data. The output layer consists of one node, which produces a single output for each input row.

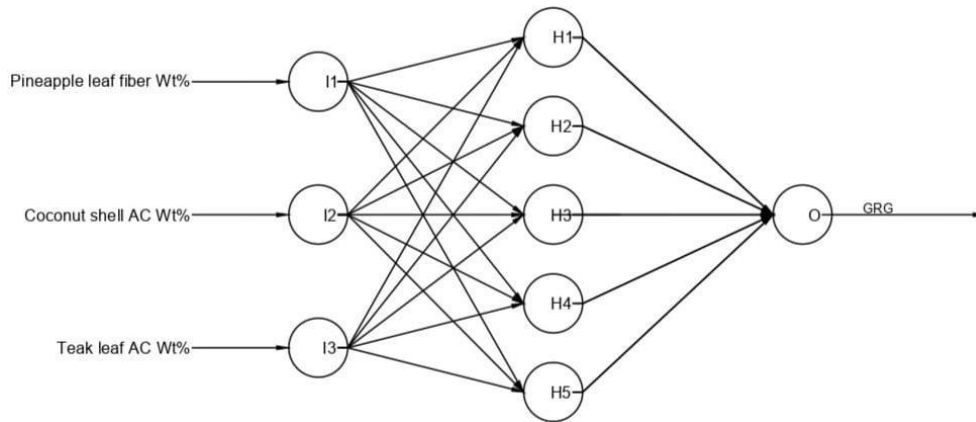


Fig 6: Design of Grey Relational Grade using ANN

The model uses the sigmoid activation function to apply a non-linear transformation to the input data in the hidden layer. The sigmoid function maps any input value to a value between 0 and 1, which allows the model to learn non-linear relationships in the data. The derivative of the sigmoid function is used in the back propagation algorithm to update the weights of the model during training.

During training, the model performs forward propagation to compute the output of each neuron, and then uses back propagation to update the weights of the model based on the error between the predicted output and the actual output. The learning rate and number of epochs are hyper parameters that control the speed and accuracy of the training process.

After training, the model is evaluated on a validation set to assess its performance. The mean absolute error is used as the evaluation metric, which measures the average absolute difference between the predicted output and the actual output. The goal of the model is to minimize this error, which indicates how well it can generalize to new data.

The assessment of a proposed model involved training it on 9 experiments and testing its accuracy on three additional experiments, namely the 3rd, 6th, and 9th. The results of these experiments were then compared to the predicted results from the model, and the comparison revealed that they were quite similar.

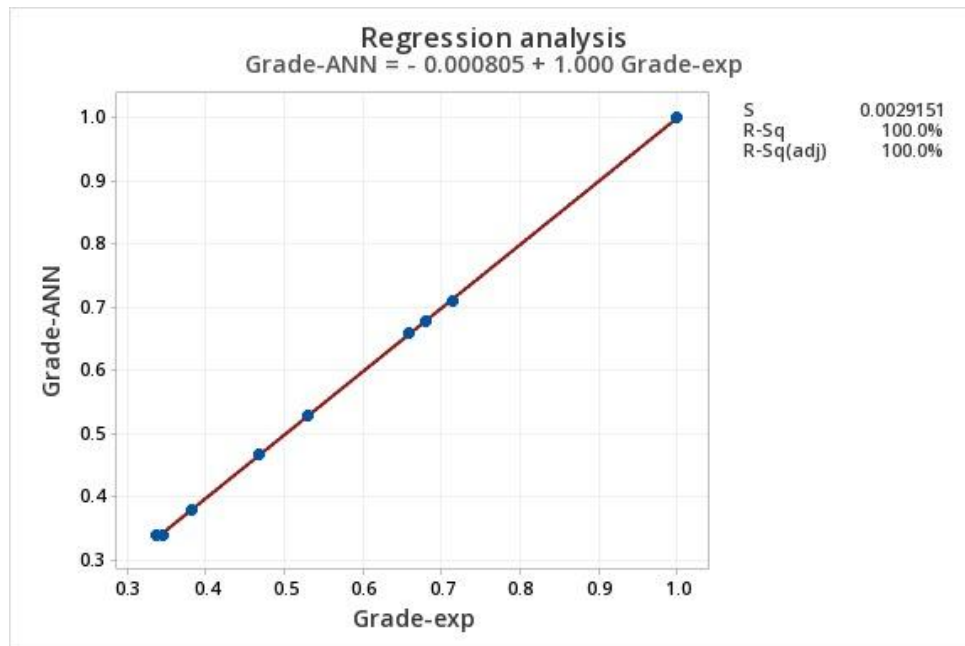


Fig 7: Experimental and predicted result relation using Minitab.

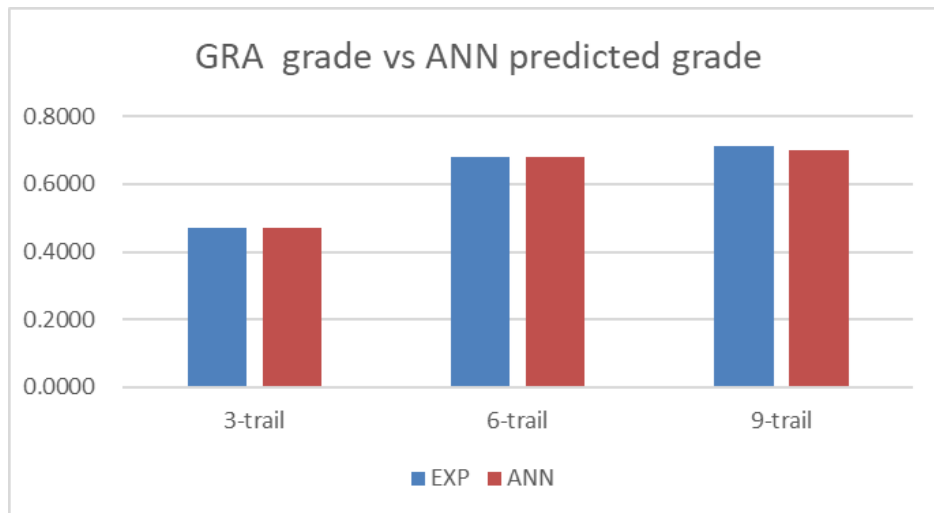


Fig 8: Comparison of Experimental and predicted results.

Moreover, a regression analysis was carried out to gauge the strength of the relationship between the predicted and actual results. The R-value, which is a metric that measures the extent of the correlation, was found to be 99.998%. This suggests that the model is highly precise and can accurately forecast the outcomes of similar experiments.

However, it's essential to keep in mind that evaluating a model is a continuous process that requires ongoing testing and refinement to ensure its robustness and reliability. Additionally, it's crucial to consider the model's limitations and assumptions and to validate its performance on diverse datasets.

Conclusion:

In this study, the mechanical performance of pineapple leaf fiber, coconut shell, and tectonagrandis leaf in epoxy polymer composites was evaluated. The developed composites' overall mechanical properties were optimized using the hand layup method as well as the Taguchi-based, GRA, and TOPSIS methods. Three factors, namely pineapple fiber (0–30 wt%), tectonagrandis (0–30 wt%) and coconut shell (0–30 wt%), were included in the study. An L9 orthogonal array was used to determine the optimized results, and the findings are presented below.

The response table generated by the GRA and TOPSIS methods indicated that the incorporation of pineapple fiber had the greatest influence on improving the overall mechanical properties of the epoxy-based composites, while tectonagrandis and pineapple fiber had a comparatively lower impact.

The maximum mechanical property using the GRA and TOPSIS method was observed in the combination of 15 wt% pineapple fiber, 30 wt% tectonagrandis and 30 wt% coconut shell.

Incorporating pineapple fiber and tectonagrandis improved the compatibility between reinforcement and matrix phases, resulting in enhanced tensile, compression, and impact strength in the epoxy-based composites.

The combination of 30 wt% C, 30 wt% T, 15 wt% P, which was determined to be the best combination through GRA and TOPSIS methods, showed significant improvements in mechanical properties due to the combination of the fibers and tectonagrandis.

The study demonstrated a strong correlation between the experimental and predicted GRG using an Artificial Neural Network (ANN). Specifically, the results indicated that a network topology of 3-5-1 (3 input nodes, 5 hidden nodes, and 1 output node) had a high level of predictability. These findings suggest that the ANN model can effectively analyze the factors that influence mechanical properties, as measured by the GRG.

Overall, the findings of this research work provide valuable insights into the optimization of natural fiber composites for lightweight applications, which could potentially reduce the environmental impact of traditional materials while also improving performance.

References

- [1] Taer, E., Melisa, M., Agustino, A., Taslim, R., SintaMustika, W., & Apriwandi, A. (2021). Biomass-based activated carbon monolith from Tectonagrandis leaf as supercapacitor electrode materials. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 1-12.
- [2] Taer, E., Agustino, A., Awitdrus, A., Farma, R., & Taslim, R. (2021). The synthesis of carbon nanofiber derived from pineapple leaf fibers as a carbon electrode for supercapacitor application. *Journal of Electrochemical Energy Conversion and Storage*, 18(3).
- [3] Taer, E., Taslim, R., Putri, A. W., Apriwandi, A., & Agustino, A. (2018). Activated carbon electrode made from coconut husk waste for supercapacitor application. *Int. J. Electrochem. Sci*, 13(12), 12072-12084.

- [4] Amri, A., Taslim, R., &Taer, E. (2020, October). The physical and electrochemical properties of activated carbon electrode derived from pineapple leaf waste for supercapacitor applications. In *Journal of Physics: Conference Series* (Vol. 1655, No. 1, p. 012008). IOP Publishing.
- [5] Manjakkal, L., Franco, F. F., Pullanchiyodan, A., González- Jiménez, M., & Dahiya, R. (2021). Natural Jute Fibre- Based Supercapacitors and Sensors for Eco- Friendly Energy Autonomous Systems. *Advanced Sustainable Systems*, 5(3), 2000286.
- [6] Sumesh, K. R., &Kanthavel, K. (2022). Grey relational optimization for factors influencing tensile, flexural, and impact properties of hybrid sisal banana fiber epoxy composites. *Journal of Industrial Textiles*, 51(3_suppl), 4441S-4459S.
- [7] Taer, E., Apriwandi, A., Ningsih, Y. S., Taslim, R., &Agustino, A. (2019). Preparation of activated carbon electrode from pineapple crown waste for supercapacitor application. *Int. J. Electrochem. Sci*, 14, 2462-2475.
- [8] Ganesh, S., Keerthiveetil Ramakrishnan, S., Palani, V., Sundaram, M., Sankaranarayanan, N., Ganesan, S. P., *Polym. Compos.* 2022, 43(1), 130. <https://doi.org/10.1002/pc.26362>.
- [9] Amri, A., Taslim, R., &Taer, E. (2020, October). The physical and electrochemical properties of activated carbon electrode derived from pineapple leaf waste for supercapacitor applications. In *Journal of Physics: Conference Series* (Vol. 1655, No. 1, p. 012008). IOP Publishing.
- [10] Seiko Jose, Rajna Salim & Lakshmanan Ammayappan (2016) An Overview on Production, Properties, and Value Addition of Pineapple Leaf Fibers (PALF), *Journal of Natural Fibers*, 13:3, 362-373, DOI: 10.1080/15440478.2015.1029194